Models and Methods for Adaptive Management of Individual and Team-Based Training Using a Simulator

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Abstract. Research of adaptive individual and team-based training has been analyzed and helped find out that both in Russia and abroad, individual and team-based training and retraining of AASTM operators usually includes: production training, training of general computer and office equipment skills, simulator training including virtual simulators which use computers to simulate real-world manufacturing situation, and, as a rule, the evaluation of AASTM operators’ knowledge determined by completeness and adequacy of their actions under the simulated conditions. Such approach to training and re-training of AASTM operators stipulates only technical training of operators and testing their knowledge based on assessing their actions in a simulated environment.

1. Introduction
In fact, this approach leaves out any identification of their knowledge and skills of simulating organizational and manufacturing situations and taking efficient managerial decisions; it doesn’t enable any identification and assessment of their knowledge on the basis of multi-informational and least loss-making methods and information technologies. Hence the problem is to research and develop a methodology for systemic identification of professional problem-focused knowledge acquired by employees operating adaptive automated systems of training management (AASTM operators), which shall also further the theory and practice of the intelligence-related aspects thereof. A robot solves this problem as a general problem of matching mathematical knowledge models as prototypes to the formalized system of knowledge an AASTM operator as a system image [1-3].

Virtual operator training based on an AASTM simulator makes it less time-consuming and resource-intensive to obtain and master the required skills. This is achieved by eliminating the negative consequences of the risk factors inherent in the in-situ education and training of water transport specialists. This enables training of water transport specialists (WTS) without any significant financial losses. The fundament of the process is a direct linking of theoretical knowledge in automated industrial fishing and fishing ship navigation to the practical requirements. Before a WTS can use a simulator, they should complete theoretical learning to have a perfect comprehension of training tasks and objectives; they should also be able to use the best automated fishing practices of crews navigating the Azov-Black Sea Basin. To solve this problem, we have, as a part of our research,
designed a scientific problem to create methods for adaptive management of individual and team-based training using a simulator.

The aim of the thesis is to research and develop methods for adaptive management of individual and team-based training using a simulator so as to facilitate the training of the Azov–Black Sea fishing fleet crews.

2. Equipment and devices used in studies
To solve the problems stated in the thesis, we have employed both systematic and situational approach as well as: control theory methods to state the decision making problem; similarity theory to construct a formal model of the system; probability theory apparatus, fuzzy and rough sets to enable the information system to process the inputs; situational control theory methods to construct a joint activity model; algebraic rings and graph theory to formalize the network model for knowledge representation and the tree structure consistency model; machine learning methods to solve the problem of data storage narrowing; adaptive planning methods to solve the activity planning problem.

The research object is the process of adaptive management of WTS training involving a professional maritime industrial bioresource extraction simulator [3-5].

The research subject matter is the methods for adaptive management of individual and team-based training using a simulator.

3. Results and discussion
The monitoring subsystem (WTM-SITT) provides a flow of observed system parameters of the joint activity model as well as a total of event flows for WTM-SITT; its operation is based on sensor measurements. A dynamic maritime object has a number of data sources of various accuracy, which provide navigation data (radar, hydroacoustic, sound ranging equipment, video cameras, etc.). In most cases these data are duplicated, for example, by the automated identification system, the radar equipment, and by visual observation. Thus, observing the navigational situation results in excessive data, which makes data processing more time-consuming and may cause delays in identifying a hazardous situation.

Consequently, the monitoring system signals the emergence of significant events, which enables the WTM-SITT and the joint activity model to solve their specific problems only most of the time. At certain moments of time $t_k$, measurements are made, and a vector of motion parameters $x^i_k$ is recorded for each maritime dynamic object (MDO) $A^i$:

$$ x^i_k = \left\{ K_i, V_i, X_i, Y_i, \phi_i, \alpha_{ji}, l_{ji} \right\} $$

where $X_i, Y_i$ is the MDO $A^i$ spatial coordinates; $K_i, V_i$ are the direction and speed of the MDO $A^i$; $\phi_i$ is the MDO angular velocity $A^i$; $\alpha_{ji}$ is the bearing to $A^j$ from $A^i$; $l_{ji}$ is the distance from $A^i$ to $A^j$.

As a result of monitoring, events like “change of direction $A^i$”, “change of speed $A^i$” are recorded, with the significant events selected from the flow:
- MDO direction change;
- MDO speed change;
- MDO entering the interaction area;
- MDO leaving the interaction area.
As monitoring is performed at a specific discretization (as a rule, every 30 seconds), WTM-SITT generates event flows providing the basis for a further analysis of situation dynamics to forecast possible WTS actions and, consequently, possible changes in MDO routes [6-8]. Meanwhile, observation of how the parameters of motion $A_i$ alter enables: case-based determination of the scenario $\Sigma_{A_i}$ this MDO is to run; suggesting the possible plan $\Pi_{A_i}$ and forecasting its route $\Phi(A_i)$. Using possible activities (plans) of observed situation disturbances, one can build control procedures $\Omega$ including a control action scenario to compensate them by maneuvering.

Key classification characteristics of a ship (MDO) are presented Table 1. Classifying based on $K^2$ makes sense only for moving targets, whereas classification on the basis of $K^3$ and $K^4$ is relevant for approaching targets as outgoing and equally spaced targets are non-hazardous by definition. Classification based on $K^5$ is made for a set of hazardous and potentially hazardous targets, and the target priority value $P_{0i}$ (corresponds to $\kappa_{\Sigma}$) is generated on the basis of a fuzzy controller. Classification based on $K^6$ is made from the standpoint of possible changes in the MDO motion parameters: if no change in $(K_0,V_0)$ renders the object hazardous, it is classified as non-restrictive, and vice-a-versa.

Classification based on the spatial position $K^7$ is of particular importance as it is connected with clustering in case search in WTM-SITT with the following main criteria of context similarity: number of disturbances; spatial position of disturbances; motion parameters of disturbances. To simplify the search of similar situations, the classification $K^7$ is performed according to the chart in Figure 1.

Controlled space is divided into sections numbered within the quadrants, each equal to $30^\circ$ as well as into circle areas $A$, $B$, $C$ and $D$ separated by the assumed borders of the areas $D_{0i}$, $D_{s}$ and $D_{u}$ according to $K^4$. MDO location is assigned to a certain sector and is specified as its identifier.

| Classification | Characteristic | Value | Class |
|---------------|---------------|-------|-------|
| $K^1$         | $V_i$, $\dot{V}_i$, $\dot{K}_i$ | $(V_i > 0) \land (\dot{V}_i = 0) \land (\dot{K}_i = 0)$ | Immobile |
|               |               | $(V_i > 0) \land (\dot{V}_i > 0) \lor (\dot{K}_i > 0)$ | Mobile maneuvering |
| $K^2$         | $\dot{D}_{0i}$ | $\dot{D}_{0i} > 0$ | Outgoing |
|               |               | $\dot{D}_{0i} = 0$ | Equally spaced |
|               |               | $\dot{D}_{0i} < 0$ | Approaching |
| $K^3$         | $D_i$, $T_i$  | $(D_i \leq D_z) \land (0 < T_i \leq T_z)$ | Hazardous |
|               |               | $(D_i \leq D_z) \land (T_i > T_z)$ | Potentially hazardous |
|               |               | $(D_i > D_z) \land (T_i > T_z)$ | Non-hazardous |
| $K^4$         | $T_i$         | $T_i > T_z$ | MRA of unrestricted motion |
|               |               | $T_i < T_z$ | MRA of a timely maneuver |
|               |               | $T_u > T_i \leq T_z$ | NRA of a delayed maneuver |
|               |               | $0 < T_i \leq T_z$ | MRA of an extreme maneuver |
| $K^5$         | $P_{0i}$      | $P_{0i} = 0$ | Of equal priority |
|               |               | $P_{0i} = 1$ | Passive |
|               |               | $P_{0i} = -1$ | Active |
To classify targets in compliance with $K^3$, $K^4$, $K^6$, $K^7$, it is necessary to estimate the values of safe area borders, particularly $T_z$, $T_s$, $T_u$, as well as the values $D_z$, $D_s$, and $D_u$ corresponding thereto at a constant speed of the MDO. Safe area borders are determined as approximated interval estimates set by the border areas of $H_{BND}^1$, $H_{BND}^2$, $H_{BND}^3$ in terms of the rough set theory:

\[
POS_{H^3} = NEG_{H^2} \cup BND_{H^2} \cup POS_{H^2},
\]
\[
POS_{H^2} = NEG_{H^1} \cup BND_{H^1} \cup POS_{H^1}.
\]

(2)

The interaction space $C'$ is divided into areas (see Figure 2) by $K^4$ using the approximate estimates of safe borders $\tilde{D}_z$, $\tilde{D}_s$, and $\tilde{D}_u$.

Being aware of the specified estimates and assuming the MDO speed is constant within the current time period, it is possible to determine the values $\tilde{T}_z$, $\tilde{T}_s$, and $\tilde{T}_u$. As there are no formal methods for getting reliable estimates of safe area borders, while it is obvious such estimates recur in similar situations for the same-type disturbance classes, WITMITT uses the following principles to train finding the approximate estimates of safe area borders [9-11].
1) To represent the estimates of safe area borders, a formal rough set apparatus is used, while an estimate for each safe area border is determined by the interval:

$$\tilde{D}_z = \left[ D_{z_{\min}} ; D_{z_{\max}} \right], \quad \tilde{D}_s = \left[ D_{s_{\min}} ; D_{s_{\max}} \right], \quad \tilde{D}_u = \left[ D_{u_{\min}} ; D_{u_{\max}} \right].$$  (3)

2) An approximate estimate of a border for each area can “contract” in case of navigation data are specified and ship approaching occurs, which makes disturbance classification more accurate.

3) In a real-world setting, estimates $\tilde{D}_z$, $\tilde{D}_s$, and $\tilde{D}_u$ can be obtained by the ASTM using a case-based analysis, see Figure 3.

![Figure 3 – Safe border values determination](image)

Appropriate cases are searched made according to the next neighbor method $K_{NN}$ based on the function that assesses the similarity of the case to the currently observed situation. Calculations are made using the coordinate-based method of comparing the situation and the case in terms of context parameters.

For $t_k$, the current navigation situation is a record:

$$S_k = \left\{ t_k, n, x^W_k, \left\{ x^i_k, x^C_k, \left\{ x^{ji}_k \right\}_{j=1}^{n-1} \right\}_{i=1}^n \right\},$$  (4)

where $t_k$ is the current moment of time;

$x^W_k$ is the vector of external environment parameters at the moment $t_k$;

$x^i_k$ is the vector of MDO$^i$ motion parameters at the moment $t_k$;

$x^C_k$ is the vector of MDO$^i$ static characteristics;

$x^{ji}_k$ is the vector of relative motion parameters of $^i$ and $^j$ at the moment $t_k$.

$n$ is the number of MDOs interacting at the moment $t_k$.

4. Conclusions

Preliminary simulator-based training of a ship driver helps re-train the skills of developing tactics for navigating in the expected maneuvering area, learn the specifics of movement, and make a rational choice of motion control methods. Preliminary fishing training and the necessity to plan curved sections enables the acquisition of knowledge to solve tactic and technological maneuvering problems while also reducing the risk of facing unfavorable trawl casting.

Overview of the existing SCM and the proposed formalized models have enables the researches to design a new structure of the system for automated control of a ship during trawl casting. It was made possible by creating of an integrated hierarchic three-level system for maneuvering control as well as taking into account the specific nature of ship control at during trawl casting. The paper contains the list of measures that shall be taken to implement the PID.
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