INTELLIGENT ANALYSIS OF NAVIGATORS' MANEUVER EXECUTION BASED ON THEIR QUALIFICATION ATTRIBUTES

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Introduction. An important factor in enhancing maritime safety remains the implementation of automated and intelligent systems as additional modules within decision support systems (DSS) [1]. The ability to directly read navigation data from the monitor screen, recognize them, and generate trajectories concerning changes in the ship's course and speed provides a tool for deeper analysis. For instance, certain segments of a ship's trajectory—especially in port areas, traffic separation schemes in straits, or sections where the ship navigates along a fairway or near dangerous isobaths–exhibit consistent curves that indicate individual navigators' approaches to ship movement management [2]. Indeed, every navigator with a certain level of experience consciously follows actions and cognitive behavioral models when controlling the ship's movement [3].

Therefore, it can be noted that a ship's trajectory is conditionally divided into fragments that are subject to the strategies of the navigator controlling the vessel. To segment the ship's trajectory into these fragments, one should refer to sailing directions, the opinions of experienced captains, and instructors from navigation training centers and laboratories. Expert opinions allow for the identification of specific critical zones associated with changes in the route's leg. Subsequent analysis of movement trajectories precisely in these clearly defined zones enables the identification of how skillfully the navigator performs the maneuver (Figure 1).

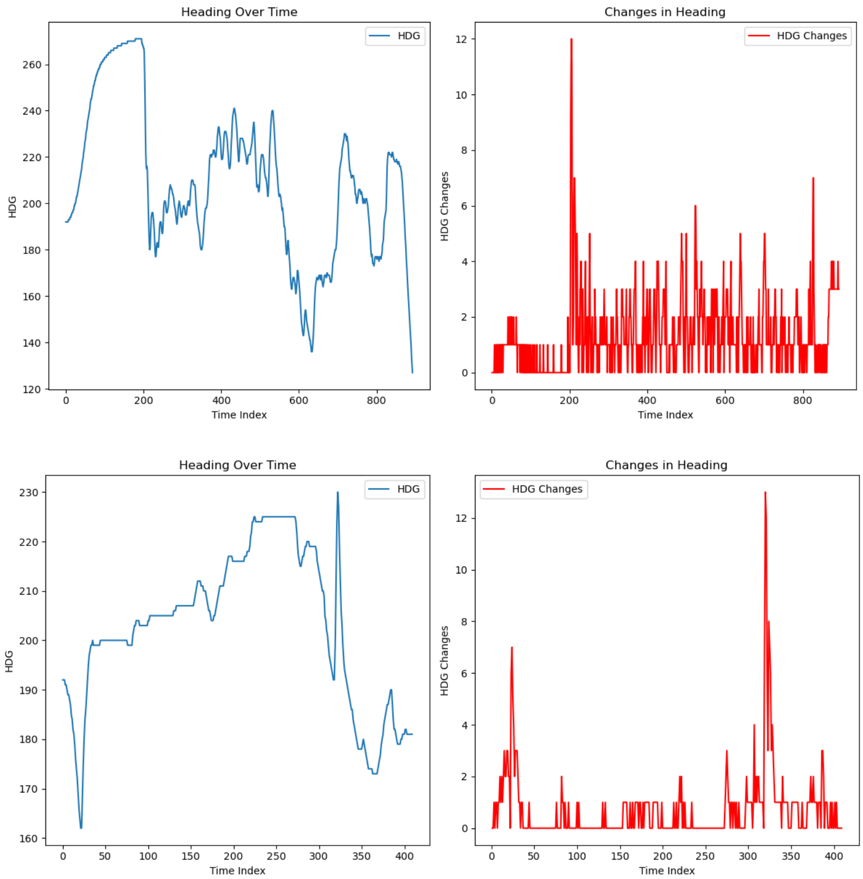

Figure 1 – Fragments of the ship's trajectory based on course and speed changes

Of course, each navigator has their own models for executing each ship movement maneuver, making direct comparisons challenging. However, safety and resource economy should primarily serve as the criteria for analysis; in this sense, all maneuver trajectories can be considered satisfactory [4].

At this stage, an opportunity arises to compare the maneuver trajectories of a selected navigator with previous ones recorded earlier (training practice, real voyages). Having a database of trajectories that are classified and correspond to specific ship control operations—and that belong to a particular navigator—allows for their comparison using neural networks. Then, based on individual trajectory fragments, it becomes possible to train a neural network to establish conformity with the current qualification level of each navigator (Figure 2).

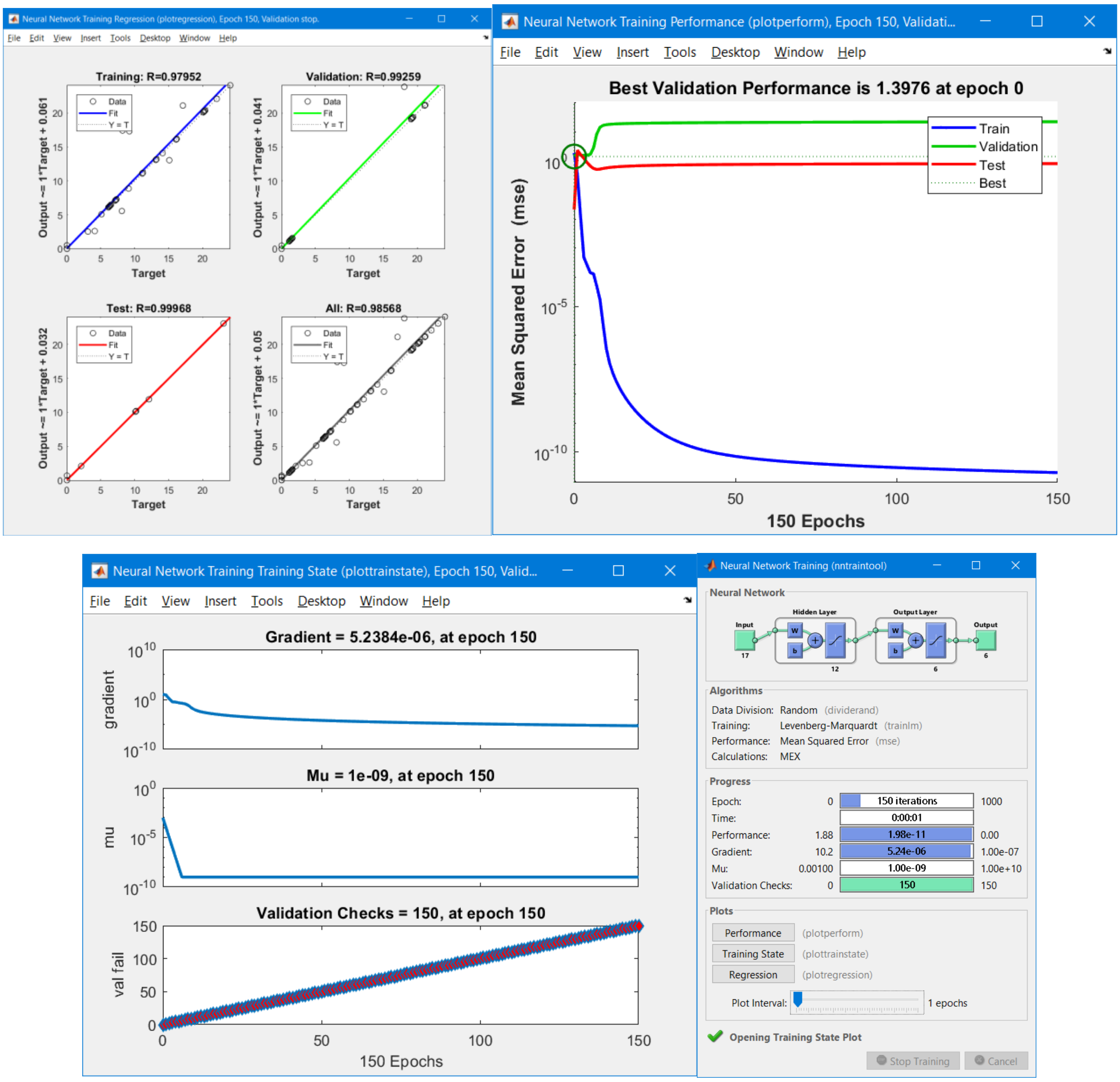

Figure 2 – Screenshots of the neural network training process based on fragment data

As we can see, appropriately selected fragment boundaries from the overall ship movement trajectory allow achieving sufficient accuracy in neural network training.

In this way, it becomes possible to compare, in real-time, the execution of a maneuver under similar navigation circumstances. This allows for predicting the conditional safety level to which the maneuver belongs (Figure 3), which in turn provides time to inform the captain or the watch officer. Identifying negative changes in the trajectory of maneuver execution enables the automated system, in addition to notifying senior officers, to switch ship movement control to autonomous mode and guide it to a safe point on the route.

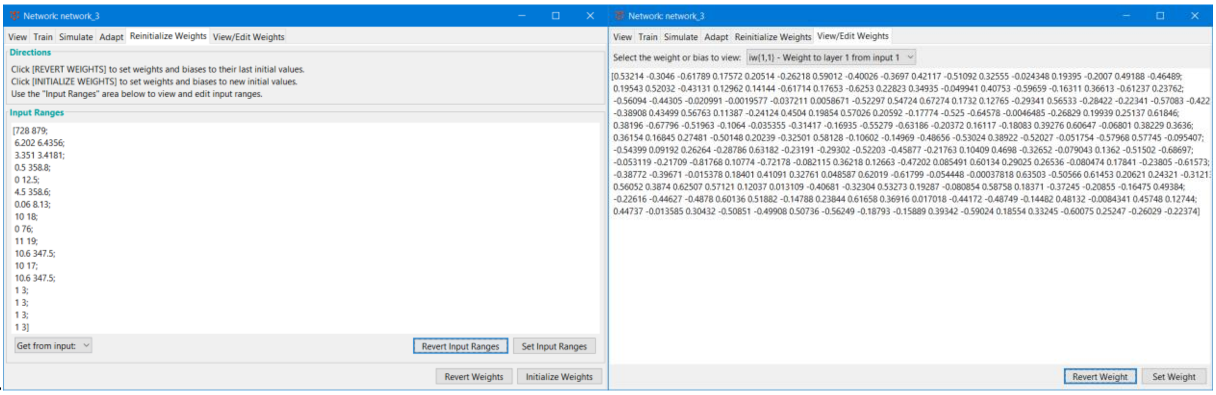

Figure 3 – Intelligent identification of the maneuver using neural network tools

Additionally, a module has been developed to determine the qualification parameters of navigators for calculating their qualification indicators corresponding to a particular maneuver in terms of safety level. The module employs mathematical and statistical methods to compute these parameters, enabling informed decisions regarding the management of the navigation watch based on a comprehensive analysis of their qualifications. Accomplishing this task ensures more efficient management of watches and navigation bridge teams and is crucial for the overall research outcome.

1. Determination of Qualification Level Qu (1):

$$Qu = \left(\sum_{i=1}^{n} \eta_i \cdot S_i \cdot w_i\right) \cdot \left(1 + \frac{\log(1 + E + C)}{T + 1}\right) \tag{1}$$

η_i – number of skills;
S_i – score for the i-th skill;
w_i – weight of the i-th skill;
E – total work experience in years;
C – number of professional training certificates (in a specific field);
T – time (in years) during which the navigator did not undergo professional training (since obtaining the last certificate).

For the calculation, we will consider η_i, where i = 3 (the most decisive skills in the current situation).

η_1 – Planning and conducting the voyage, determining the vessel's position, and the accuracy of position determination results by various methods;
η_2 – Maintaining a safe navigational watch, organization, and procedures of watchkeeping;
η_3 – Ensuring safe navigation by using information from navigation equipment and systems that facilitate the decision-making process;
η_4 – Ensuring safe navigation by using the Electronic Chart Display and Information System (ECDIS) and related navigation systems that facilitate decision-making;
η_5 – Actions during emergencies that occur while underway;
η_6 – Actions upon receiving a distress signal at sea and coordination of search and rescue operations;
η_7 – Use of the English language and the International Maritime Organization's Standard Marine Communication Phrases;
η_8 – Transmission and reception of information using visual signals;
η_9 – Maneuvering and controlling the ship under any conditions;
η_{10} – Operation of remote-control systems for the propulsion plant and engine room systems and services.

This comprehensive formula allows for combining various aspects of qualification into a single metric [5], providing a more accurate determination of the navigator's level of professionalism. This is important for correctly assessing their ability to control the ship under different conditions.

2. Model for Calculating Experience *Exp* (2).

To determine *Exp*, we take into account the number of watches in different navigation conditions, various locations where the navigator stood watch, and the different positions held. We can create an index that aggregates these data into one formula:

$$Exp = L_j \cdot A_k \cdot \left(\frac{F_{ijk}}{\Lambda} \cdot \log\left(1 + G_{ijk}\right) \right) \cdot 100 \tag{2}$$

Where:

L_j – weight or coefficient for location j, reflecting the complexity or importance of this location in the navigator's overall experience.

A_k – coefficient for position k, reflecting the level of responsibility and complexity of duties in that position.

F_{ijk} – number of watches stood in the i-th navigation situation at location j in position k.

Λ – normalizing coefficient.

G_{ijk} – complexity rating of the i-th navigation situation at location j in position k.

This approach allows for assessing the navigator's overall experience by considering not only the number of watches but also the diversity of situations and conditions in which they have worked. The overall formula reflects how experience in different positions and locations affects the navigator's ability to effectively cope with future challenges.

3. Conditions of Navigation by Similarity of Navigation Situation, k_q (3):

$$k_q = \exp\left(\left(\mu \cdot \left(Qu - \delta\right)\right) \cdot \left(1 + a \cdot D + b \cdot \log\left(1 + Tr\right) + c \cdot W\right)\right) \Big/ 1000, \tag{3}$$

where:

Qu – navigator's qualification score;

μ – parameter adjusting the curve of the exponential function exp;

δ – coefficient accounting for instantaneous deviations from the course due to the navigator's unfamiliarity with ship control rules;

D – complexity category of the navigation area;

Tr – traffic intensity;

W – weather conditions;

a, b, c – parameters that determine the weight of the influence of each parameter D, Tr and W.

4. Determination of Overall Qualification *Qual* (4)

$$Qual = \left(Qu^{\alpha} \cdot Exp^{\beta} \cdot kq^{\gamma}\right)^{\frac{1}{\alpha+\beta+\gamma}}, \tag{4}$$

where α, β, γ – are weights for the influence of each component on the overall qualification.

Conclusions. This paper proposes a new approach to evaluating navigators' qualification attributes by integrating mathematical models and neural networks. A methodology for real-time identification of navigators' maneuvers has been developed, based on comparing the current trajectory with previous data stored in a trajectory database. A comprehensive formula for qualification assessment is proposed, which considers skills, work experience, number of certificates, training duration, and other significant factors. This enables more effective planning of navigation watch management and ensures maritime safety.

The developed approach includes analyzing critical zones of the ship's route, which allows for detecting deficiencies in the navigator's qualifications and promptly responding to hazardous situations. The use of neural networks increases the accuracy of maneuver assessments, enabling the prediction of the safety level of executed operations. Practical implementation of this methodology will contribute to the automation of ship management and optimization of the navigation team's composition.

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