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Application Perspective of Digital Neural Networks in the Context of Marine Technologies

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ABSTRACT: This study is focused on the issue of digital neural networks' implementation in the context of maritime industry. Various algorithms of such networks in the terms of the marine technologies have been reviewed in the current study in order to evaluate the effectiveness of the methodology and to propose a new concept of an artificial neural network's application in this way. Fire-detection system simulation based on the thermal imagers' data input had been developed to assess the efficiency of the concept suggested with a multi-layer perceptron (MLP) algorithm integrated into the designed 3d-model.

1 INTRODUCTION

Although the concept of artificial neural networks is known starting from the past century, nowadays it found a new breath due to modern computer technology development: software/hardware resources and capabilities. Artificial neural networks are related to many disciplines: neurophysiology, mathematics, statistics, physics, computer science and engineering. They find their application in various fields such as modeling, time series analysis, pattern recognition, signal processing and control due to their data learning ability.

The purpose of the current research is to review and evaluate the usage of digital neural networks (DNN) in the context of the maritime industry by analyzing existing studies to propose new concepts in this matter.

2 ANALYSIS OF EXISTING MODELS AND RESEARCH METHODOLOGY

Neural networks are one of the areas in the field of artificial intelligence, based on attempts to reproduce the human nervous system, namely: the ability to learn and correct errors, which should allow simulating, albeit rather roughly, the work of the human brain. A neuron is a base element of DNN. The basic structural scheme of the network's j – neuron is presented in figure 1.

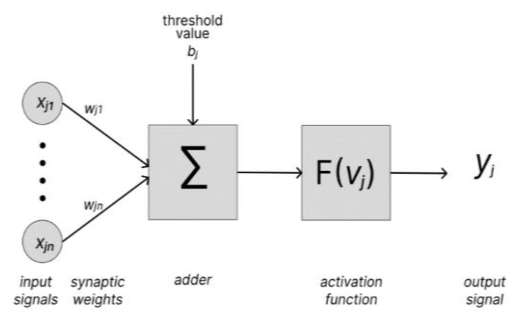

Figure 1. Neuron model

Different studies already proposed and/or reviewed the concept of DNN models, which are applied or may be applied to the maritime industry.

Autonomous ship control and vessel motion prediction present a widely pursued area of research for already more than 30 years. Autonomous shipboard navigation in channels was considered in [18] using a neural network consisting of an adaptive critic element (ACE) and an adaptive search element (ASE). ASE was responsible for studying the channel area while ACE evaluated the ASE performance, tending to predict potential failures in navigation. The developed model showed good results through software simulation with graphical feedback.

A combining density-based spatial clustering of applications with noise (DBSCAN)-based Long Short-Term Memory (LSTM) model, as an extension of recurrent neural network (RNN), was developed for vessel trajectory prediction, where DBSCAN was used to cluster vessel tracks from automatic identification system (AIS) data, and LSTM was used for training and prediction [21]. The resulting predictions of the proposed model showed a 2% advantage over other models in the study. The nonlinear autoregressive exogenous (NARX) network was used as the core of the ship motion prediction framework in the study [7]. The advantage of the NARX network's long-term prediction ability a multi-step-ahead prediction was realized under the hybrid learning strategy and experimental results showed the efficiency of the NARX network in generating the data-driven model for ship motion prediction. The use of multi-layered perceptron (MLP) was discussed in the study [22] for vessel motion prediction in specified conditions, showing good agreement with the expected results. To enhance optimization and multi-criterial automatic design of ships in terms of fast and simultaneous analysis of many design solutions within a similar time interval, the work [2] presented a neural network implementation for the assessment of ship manoeuvrability qualities. The back-stepping method using a neural network to approximate the nonlinear ship course control system was used in research [23]. A neural network was utilized to approximate nonlinear terms in the ship model. To verify the effectiveness of the proposed control algorithm MATLAB simulations were carried out.

NN application perspectives were also reflected in the mooring lines' condition monitoring. In this way, the work [12] focused on the development of a DNN-based damage detection approach with floater responses for mooring lines with even local damage in the tension leg platform. Simulation data was used for DNN training, validation, and testing. Another study [9] used RNN for effective analysis of the time-series response data employed for damage detection. The results of the RNN-based catenary mooring line damage detection approach proposed confirmed the efficiency of the RNN model in comparison with results obtained in [12]. Another research [3] highlighted the issue of the mooring lines' complex behavior and a Radial Basis Function (RBF) neural network was proposed for damage with a modelling method based on Rod theory and the Finite Element Method (FEM). In order to improve the modelling accuracy, boundary conditions uncertainty was applied using Submatrix Solution Procedure (SSP) and a round-off error is removed by SSP. The described method showed 65% higher performance than the Fuzzy method and 13% percent higher performance than the conventional one.

The use of neural networks is also being actively integrated into the development of autonomous ship berthing control. In the following works [3-6] an automatic berthing controller from the neural network technology was designed via virtual window theory algorithms, nonlinear programming, as well as the PD hybrid control. The effectiveness of the model was verified from the free-running model test. In [16], the artificial neural network algorithm was used to establish an automatic berthing model and the berthing process of the ship was divided into two stages: the proceeding and deceleration stage, and the turning and berthing stage. The paper [7] highlights four major challenges for the implementation of ANN controller for ship berthing. The problem of auto-berthing control was considered in [17], where a neural network (NN) adaptive approach based on the navigation dynamic deep-rooted information (DRI) was proposed to resolve the uncertainties caused by unknown ship dynamics and external disturbances. The dynamic surface control (DSC) and the minimum learning parameter (MLP) techniques were used to minimize the computational load of the adaptive NN control scheme. Simulations were carried out on a vessel to verify the effectiveness of the proposed model. The study [13] is devoted to the development of an automatic ship`s berthing system, by using the RNN for a non-linear optimal feedback controller. The Proposed system was evaluated through extensive computer simulations and an actual experiment was carried out. MLP in conjunction with the back-propagation algorithm was applied in a study [1] to develop a feed-forward controller using a non-simplified mathematical model for modelling an automated ship berthing controller.

Several works, such as [10, 14, 19], present the models related to fire-detection systems implementing various DNN algorithms. Research [10] describes a real-time fire system based on grey-fuzzy algorithms. A fire detection algorithm, which uses a pyroelectric infrared motion sensor (PIR) and DNN is proposed in [19]. Data collected from the sensor was processed for further DNN training. According to the described study, such a model showed efficient results during tests and was capable to detect not only fire but also human motion.

In the study [14] fire datasets from laboratory experiments are presented by authors for further processing of these datasets using machine learning techniques.

The current study is focused on the DNN application in shipboard fire-detection systems, namely, in the processing of thermal data received from thermal imaging devices. Cargo fire simulation inside the container vessel's cargo hold was modelled for further experiments and data collection within the task. As the cargo holds configuration, especially cross-decks' arrangement, may differ depending on a vessel's design, and there is a possibility, that some difficulties may be encountered at the imagers' allocation stage (e.g. blind zones), an artificial neural network may provide a solution for containers' thermal condition control over the cargo hold, estimating areas of an issue. The allocation diagram with positions of thermal imagers, correspondent numbers of containers, bulkheads and blind zones is presented in figure 2. Simulation has been carried out using instruments of Unity IDE and C# programming language capabilities.

As the DNN for data processing, a multi-layer perceptron has been chosen to evaluate the efficiency of the formulated idea in the first approximation. In this way, such an evaluation could be stated as an objective within the purpose of the current research.

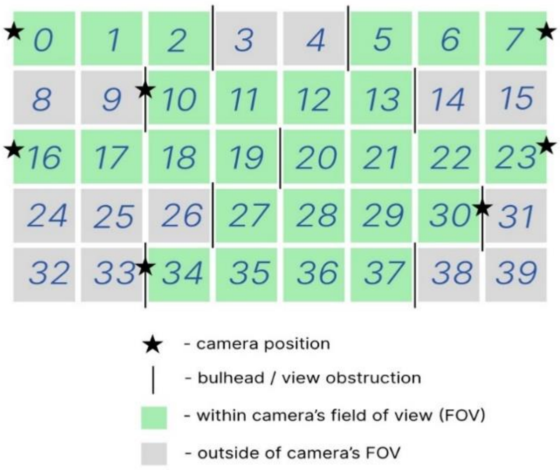

Figure 2. Allocation diagram sample

2.1 *DNN implementation*

Multi-layer perceptron could be applied for solving a wide variety of tasks, herewith its training may be carried out by means of error back-propagation algorithm [8, 20]. Such an algorithm in its turn is based on the error-correction learning rule. This method of training supposes forward and backward passes through all the DNN's layers (see fig. 3).

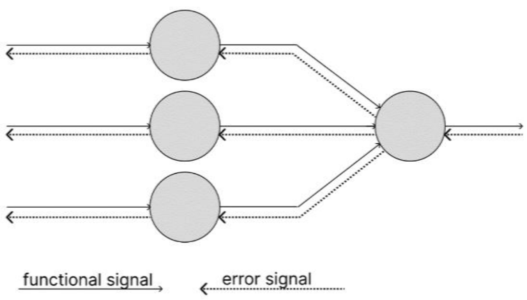

Figure 3. Forward and backward pass

During the forward pass an input data vector is sent to the sensor nodes with further spreading among the network, resulting in a set of output signals, which may be interpreted as a network reaction onto the initial input. An error signal is generated by the deduction of actual output from the desired one, setting up all the synaptic weights in accordance with the error-correction rule during the backward pass. Consequently, it is spreading in the direction opposite to one of the synaptic connections.

A schematic diagram of the network being used during the current experiment is presented in figure 4.

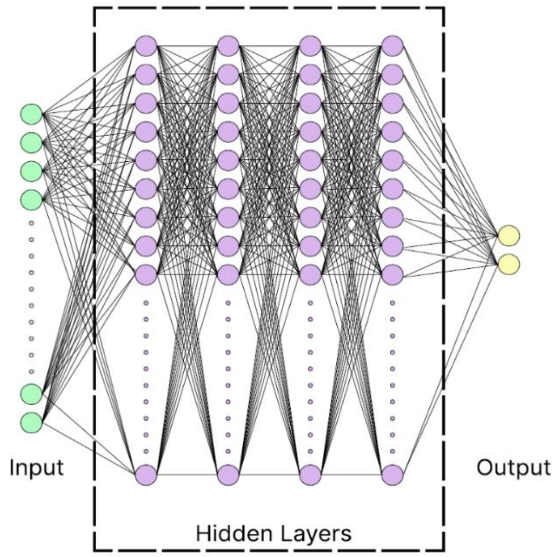

Figure 4. Multi-layer perceptron model

The input layer of the DNN used in the research consists of an array with a length of fourteen elements. These elements are seven maximum temperature values of containers in the simulated thermal imagers' field of view (FOV), allocated in accordance with the defined pattern, and their correspondent locations (i.e. seven temperatures plus seven container numbers, distributed in a sequence from left to right and from up to down as shown in fig. 2).

To normalize data input for further processing next equation has been used:

$$n_i = \frac{(x - x_{\min}) \cdot (d_2 - d_1)}{x_{\max} - x_{\min}} + d_1, \tag{1}$$

where
n_i – normalized data,
x – data to be normalized,
[$xmin; xmax$] – interval of x values,
[$d_1; d_2$] – interval of normalized values.

Actual data processing is carried out inside of hidden layers. There are four layers of this type that were set for the current task. Quantities of layers and neurons are defined in an experimental way to show the most accurate outputs.

Sigmoidal nonlinearity has been used as an activation function and it is determined as a logistic one:

$$y_j = \frac{1}{1 + \exp(-v_j)}, \tag{2}$$

where
y_j – neuron's output;
v_j – weighted sum of all synaptic inputs for neuron j plus neuron's threshold value.

For the training purpose, the output data was set as an array with a length of two elements: the maximum temperature value in the scene and its location. The minimum temperature value for the experiment was defined as the value of zero degrees Celsius and considered as sufficient within the framework of the task. The DNN was integrated into the 3d simulation model in order to perform the experiment.

2.2 *Simulation modelling*

The designed simulation consists of 3d-container models (see figure 5) with a fire source randomly located inside one of them. Each side of the container is divided into a specified quantity of segments. The color of each segment depends on the current temperature value inherent to it. Temperature intervals for the color palette may be set manually by the operator. Detailed heat exchange simulation between the segments is a matter of separate research and a linear dependency at each frame is considered as sufficient within the set task.

Figure 5. Container 3D-model

To achieve the set objective, the next initial conditions have been applied to the model in order to select only necessary and sufficient data for the fulfillment of the experiment:

- only 40-feet containers are used in the simulation;
- cargo containers are considered empty to avoid any additional issues, which may be assumed as unnecessary within the stated task, except the one carrying the fire source;
- containers' quantity of 40 units is considered sufficient to provide a thorough examination of the simulation process;
- thermal imager's allocation should ensure the most effective coverage over the row-tier area;
- thermal imagers are allocated in the cross-deck areas of the cargo hold (see figure 6).

It should be clear, that the color palette of the temperature distribution, shown in figure 6, is demonstrated for better visualization of the process and it does not fully reflect a real thermal image.

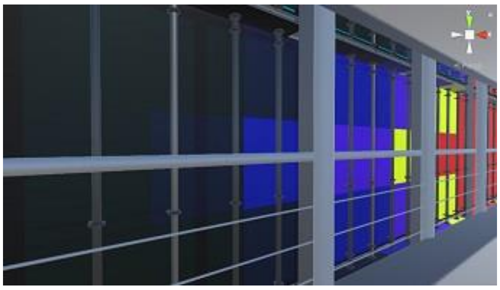

Figure 6. Allocated camera view sample

3 RESULTS OVERVIEW

During the experiment, it was found, that readings of at least three thermal imagers in the vicinity of the fire source are necessary to obtain adequate results. Their referent positions are also important in this matter and the most accurate results have been shown when the desired container had been enclosed in a triangle with vertices inside of the sensors' FOV.

As the DNN's output values belong to the interval [0; 1], their standard form may be obtained by expressing x from (1):

$$x = \frac{(n_i - d_1)\cdot(x_{\max} - x_{\min})}{d_2 - d_1} + x_{\min} \tag{3}$$

Training of the MLP was carried out using about seventy-five data sets received from the developed 3d-model (three data sets of various temperature distributions at different time points per twenty-five containers).

The results of five measurement series are brought to the table 1. Presented cases have been chosen as those which fairly reflect the outputs of the experiment in terms of summarizing the unique conditions for the placement of ignition sources in the context of data processing within the framework of the task. In four of five presented cases a temperature error does not exceed the value of five degrees Celsius (corresponds to about 90% of all cases, i.e. including those not shown in table 1), and, in general, values do not exceed the limit of ten degrees. As the importance of referent positions has already been mentioned, in this way it should be noted that only in three of five presented series the DNN was able to accurately define desired fire source position located inside of blind zones (corresponds to about 71% of all cases, i.e. including those not shown in table 1). In the rest of series, position's determination accuracy of blind zone container did not exceed the value of two units in any direction.

Table 1. Processing results

№	Parameters	Measurement spots			Fire Source	DNN's output
1	Imager's number	1	3	4		
	Temperature, °C	150.38	78.56	150.11	165.00	167.33
	Container number	0	10	16	8	8
2	Imager's number	4	7	6		
	Temperature, °C	127.57	126.78	64.76	138.00	133.02
	Container number	16	34	27	32	26
3	Imager's number	6	5	7		
	Temperature, °C	98.76	80.18	80.00	112.00	103.79
	Container number	30	23	37	39	30
4	Imager's number	3	2	1		
	Temperature, °C	110.34	109.98	101.75	120.00	124.13
	Container number	12	5	2	4	4
5	Imager's number	7	6	4		
	Temperature, °C	180.31	180.45	181.10	214.00	218.38
	Container number	34	27	18	26	26

4 CONCLUSIONS AND DISCUSSION

In the current research various artificial neural networks' algorithms were reviewed in the terms of their application in maritime industry: navigation, mooring operations, motion prediction, fire-fighting systems and etc. in an efficient way, and a wide variety of such an algorithms found their implementation into marine technologies: multi-layer perceptron, recurrent neural networks, DNNs on fuzzy algorithms etc. In this way, the usage of multi-layer perceptron in the concept of shipboard fire-fighting system based on thermal imagers' data has been proposed, performing the simulation modelling for the experiment.

The main objective of the current research is to evaluate the effectiveness of designed model in the first approximation by carrying out the fire source determination with its temperature value within the equipment's limits considering the blind zones of the allocated imagers' FOVs. Experiment results have demonstrated that the temperatures of the determined by MLP fire sources may be obtained with the sufficient accuracy (less than ± 10°C) with position prediction not exceeding the value of two units in any direction (of a "row-tier" area). In order to enhance the presented concept, namely, to increase the performance accuracy and to provide its application for various loading conditions and cargo holds' configurations more data should be collected and processed in order to train the DNN sufficiently. Taking into account safety and economic issues inherent to the conducting of such experiments, in order to improve the proposed concepts' performance, the enhancing of the designed 3d-model is considered necessary.

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