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Diagnostics of Ship Engines Based on Wavelet Neural Network and Image Scanning Using Programmable Logic Circuit

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ABSTRACT

The article is devoted to a diagnostic system for ship engines based on a wavelet neural network and image scanning using a programmable logic circuit and considers a method for analysing multifractal wavelet models.

The combination of wavelet neural networks with a programmable PLIC-based (programmable logic integrated circuit) real-time image processing platform has a significant potential for the purposes of non-destructive testing, which makes it possible to accurately diagnose faults and take effective measures for predictive maintenance, which in turn makes it possible to effectively increase safety and reliability of equipment and reduce maintenance costs.

The article proposes an improved approach to the diagnosis of ship engines, which is based on a wavelet neural network and image scanning using a programmable logic circuit. Wavelet packet decomposition is a method for local time and frequency analysis. It gradually refines the signal at multiple scales through scaling and conversion operations, and it can automatically adapt to the requirements of time-frequency signal analysis to focus on any detail of the signal. It has the advantage of good diagnostic accuracy for information with different noise levels, as well as high reliability since image data from multiple engine signals is used.

Keywords: water transport, ships, engine, wavelet transform, image, network, predictive maintenance.

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INTRODUCTION

In recent years, the method of analysing multifractal wavelet models has become increasingly widespread since its main function is the function of activation, formation of a neuron, combining mutual advantages, establishing automatic expansion and broadcasting. Due to these properties, multifractal wavelet models are effectively used for the analysis of non-stationary random noise, which allows them to be considered as a useful tool for signal processing in the field of fault diagnosis of various technical mechanisms and equipment, such as a ship engine.

The potential of predictive maintenance using wavelet neural networks has been widely studied for various types of sensors such as vibration, temperature, current, voltage, and imaging sensors. As part of the ongoing experiments, special attention of researchers in the field of prognosis, condition monitoring and control of the condition of complex technical systems is attracted by image analytics due to variety of information they provide [1; 2].

In the context of the above, for non-destructive testing purposes, the combination of wavelet neural networks with an PLIC-based (programmable logic integrated circuit) real-time image processing platform has a significant potential. This platform provides a powerful vision processor for a variety of high-speed, computationally intensive online image recognition and classification applications.

However, despite a wide range of works that analyse the use of images for monitoring/diagnostics of the condition of equipment and units, there is a limited number of studies that address prediction issues based on multi-signal image streams.

The indicated circumstances predetermine the choice of topic for this article.

METHODOLOGY AND OBJECTIVE OF THE RESEARCH

Many authors have worked at different times on development of methods for diagnosing faults in internal combustion engines using discrete wavelet transform and neural networks. Examples of numerous publications include works [3–8].

A number of works were devoted to engines of various modes of transport, to development and rationale of an approach to predicting equipment reliability based on graphical information, which consists of modelling streams of degradation images as a spatiotemporal process and using its parameters to estimate the time between failures of the system [9–14].

At the same time, while highly appreciating the results available to date, it should be noted that development of the theory of intelligent fault diagnosis has not yet been completed, so several difficulties and limitations arise in terms of its direct use in testing. In addition, a more in-depth analysis requires a methodology that allows one to effectively combine measurements and fault analysis, data collection, interface displays and diagnostic algorithms to make a final decision about the condition of a technical device [15–16].

Thus, *the objective* of the article is to consider the possibilities of diagnosing ship engines based on a wavelet neural network and image scanning using a programmable logic circuit.

RESEARCH RESULTS

The ship engine fault diagnosis system being considered in this study is based on information collected from various sensors, a wavelet neural network and an image processing platform, which together makes it possible to analyse the data flow, signal shape and, finally, achieve the goal of diagnosing the breakdowns that have occurred and damage [17–18]. Pic. 1 shows a general diagram of the system.

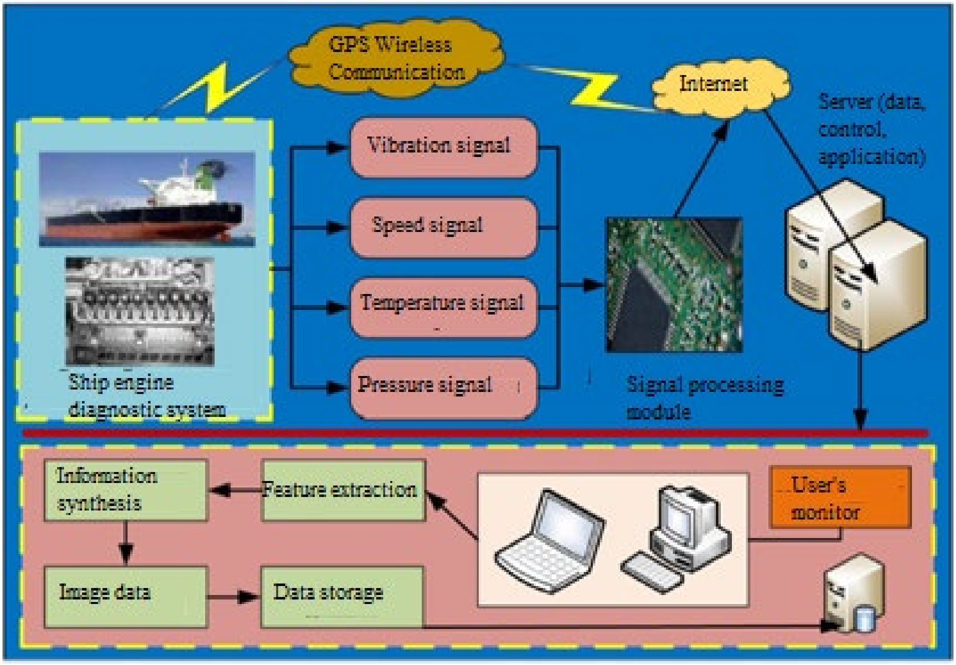
The most informative, from a structural point of view, are parameters that follow:

1. Cooling water temperature.
2. Oil pressure, temperature and consumption.
3. Gas pressure in the crankcase and at the outlet of cylinders.
4. Diesel engine load.
5. Rotational speed of the crankshaft and turbocharger rotor.
6. Fuel supply to cylinders of a diesel engine.
7. Charge air pressure.

These parameters are closely related to failures in such engine systems and mechanisms as the gas distribution mechanism, crank mechanism, fuel system, lubrication system, cooling system.

Ship internal combustion engines operate in areas with different meteorological conditions, with a changing technical condition of the main components and parts.

During operation, the technical conditions of elements of the high-pressure fuel system, cylinder-piston group, boost pressure units, diesel exhaust system and other components, parts and systems deteriorate. Deterioration of



Pic. 1. Schematic diagram of a ship engine diagnostic system [18].

the technical condition leads to a malfunction of the diesel engine (failure), expressed in a change in the values of its operating parameters beyond the limits regulated by regulatory and technical documents, or to its complete stop.

As a result of influence of operational factors the mass of air participating in the combustion process decreases; the process of fuel atomisation, mixture formation and combustion, as designed by the manufacturer, is disrupted; losses of the working fluid increase due to leaks in the parts of the cylinder-piston group on the expansion line.

Control parameters for assessing the technical condition can be:

– characteristics of the processes of fuel supply, compression and combustion in the internal combustion engine cylinder;

– pressure and temperature of air at the inlet and outlet of the turbocharger;

– vibroacoustic characteristics;

– content of wear products in the lubrication system or in exhaust gases.

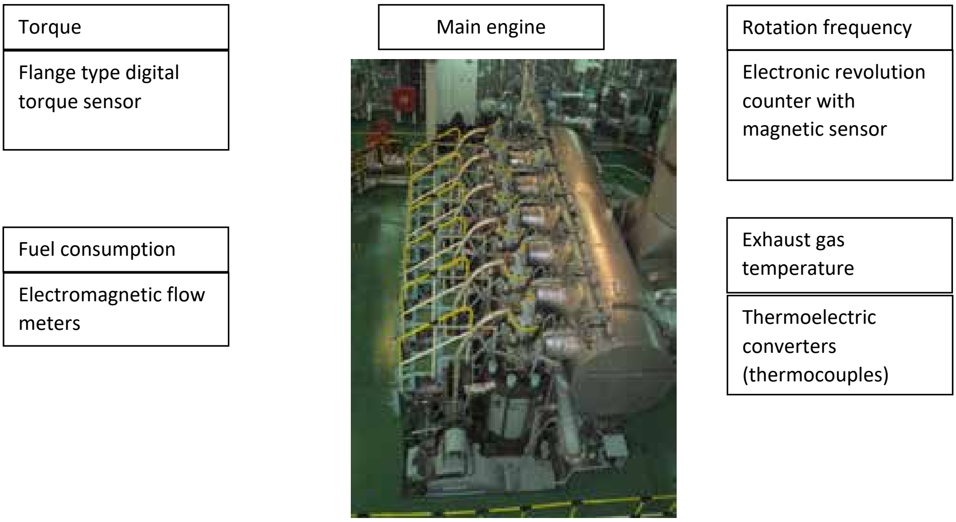
The most optimal would be a mixed control method, referring to the above characteristics.

As shown in Pic. 1, the diagnostic system is composed of engine hardware platform, signal conditioning circuit, signal acquisition board and PC terminal. The engine hardware platform includes the engine and sensors (Pic. 2). Thanks to the data acquisition board, information coming from the sensors is accumulated. The PC terminal includes LabVIEW data storage and display tools, MATLAB feature extraction and information fusion tools [19–20].

In the context of monitoring the condition of a ship engine, it is proposed to use several types of neural networks to analyse the parameters of various systems. To do this, it is possible to divide the analysis into several stages (Pic. 3). The first stage consists of filtering signals from interference and noise to isolate the real signal. This allows working with cleaner data and improves the accuracy of the analysis.

The second stage includes a direct analysis of the measured parameters, their comparison with the standard, determination of the current state and prediction of the residual life of the system elements. At this stage, various data analysis methods and machine learning algorithms can be applied to obtain more accurate results.

An important step in development of a parameter diagnostic system using neural networks is filtering of signals received by sensors and subject to various interferences and noise. Such distorted analog signals, such as acoustic or vibration signals, require the extraction of useful information. To do this, it is proposed to use neural networks for pattern recognition, such as DAE



Pic. 2. Parameters for monitoring the technical condition of a ship engine [performed by the authors].

(Denoising Auto Encoder) networks [21], ARM networks and RBF networks. These neural networks can process signals and remove unwanted distortions, allowing obtain a clean and useful signal for further analysis and diagnostics.

The decision made by the diagnostic system can be based on data in the time domain or in other domains, for example, frequency, time-frequency or scale-time domains [22–23]. Given the task of combining a wavelet neural network with a PLIC-based image processing platform, the shape of the input signal to the neural network is critical to obtain reliable data. As shown in Pic. 4, either a single motor signal or multiple motor signals obtained from the areas noted above can be used as the input signal.

According to Pic. 4 in case of single-signal models, the input signal can have one of the following forms:

• single-signal single-channel input, where the motor signal is used as a discrete one-dimensional vector or a single grayscale image, as shown in Pic. 4 *a*;

• single-signal multi-channel input, which uses colour images from 3 or 4 colour channels, as shown in Pic. 4 *b*.

For the case of multi-signal models, input data can be presented in one of the following forms:

1. multi-signal single-channel input, where all signals are either:

− placed in one picture (folded vertically), forming a large single-channel image (see Pic. 4 *c*);

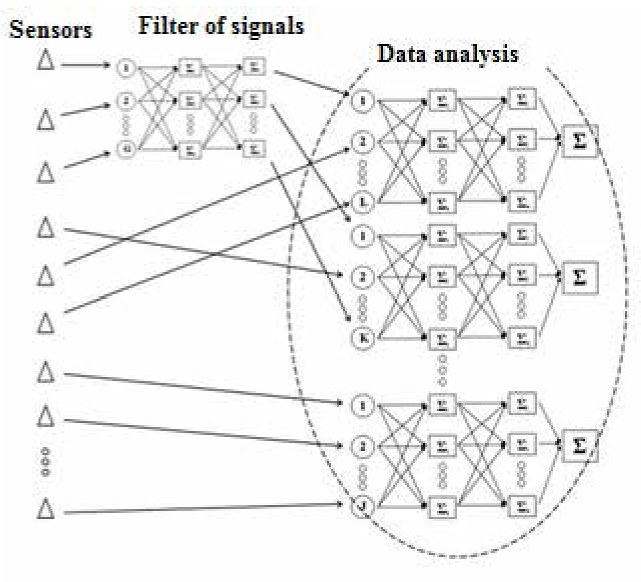
− stored as individual images but are used with multimodal networks with different convolution and subsequent smoothing paths for each signal, requiring subsequent fusion (see Pic. 4 *d*).

2. multi-channel input of several signals – each signal image is displayed in one channel, and then all the images are added to form a three-dimensional matrix, as shown in Pic. 4 *e*.

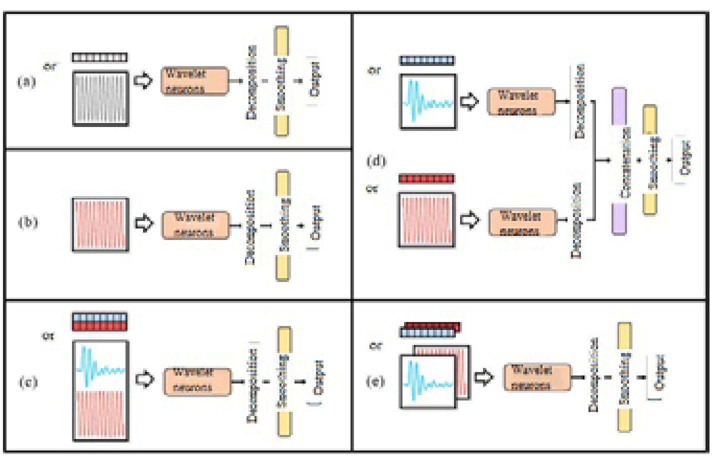
As it is known, the basic idea of wavelet neural network is to use wavelet neurons instead of traditional neurons, and then decompose the signal using multi-resolution wavelet analysis [24]. Next, it is possible to use a neural network to approximate any function, and it seems possible to use a wavelet transform and a neural network connected to each other. The wavelet neural network combines the good ability of the wavelet transform for time-frequency localisation and the ability of the neural network to self-learn and approximate functions. Due to the use of wavelet scale factors and transfer coefficients during wavelet transformations, the series after all modifications becomes more flexible and can have effective function approximation and pattern recognition capabilities.

For the wavelet generation formula $\psi(t)$, if the function $x(t)$ satisfies quadratic integrability, then the continuous wavelet transform (WT) is defined as:

$$C_\psi\left(f_s, f_t\right) = \int_{-\infty}^{\infty} x(t)\psi(t|f_s, f_t)dt\ , \qquad (1)$$



Pic. 3. Stages of preparing data for analysis by a neural network [performed by the authors].



Pic. 4. Various forms of input data for wavelet neural network [16].

in turn:

$$\psi(t|f_s, f_t) = \frac{1}{\sqrt{f_s}}\psi\left(\frac{t-f_s}{f_t}\right), \qquad (2)$$

where $\psi(t|f_s, f_t)$ – wavelet function; f_s, f_t – scaling coefficient and transfer coefficient respectively.

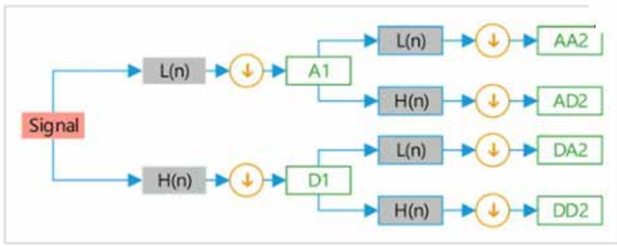
A sequence of input signals $x(n)$ of length N is sampled to obtain a discrete wavelet transform:

$$A(n|j,k) = DS\left[\sum_n x(n) l_j^*(n-2^j k)\right], \qquad (3)$$

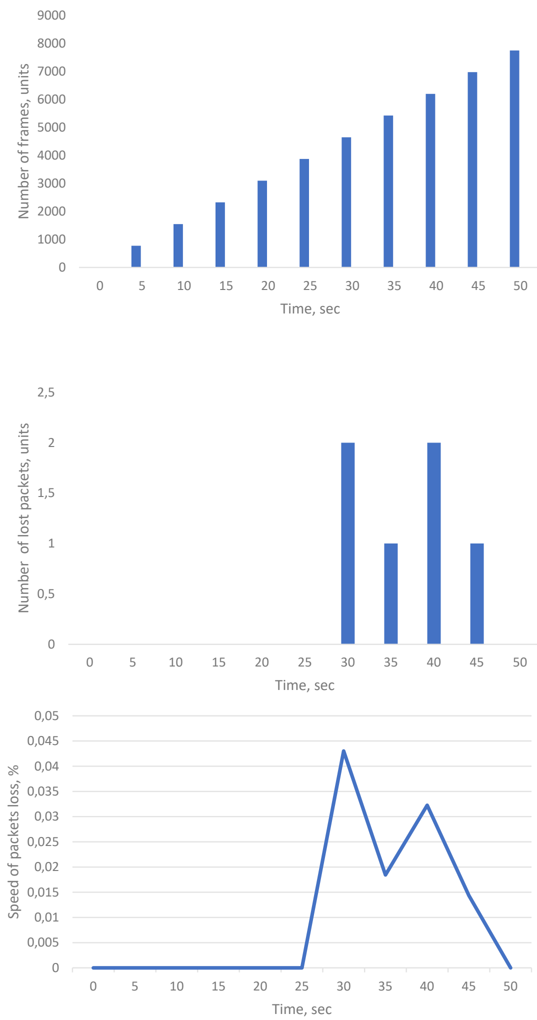
$$D(n|j,k) = DS\left[\sum_n x(n) h_j^*(n-2^j k)\right], \qquad (4)$$

where A – low frequency coefficient; D – high-frequency coefficient; $l(n)$ and $h(n)$ – low-pass and high-pass filters, respectively; $l^*(n)$ and $h^*(n)$ – conjugate functions $l(n)$ and $h(n)$ respectively; j and k – scaling coefficient and transfer coefficient respectively; DS – downsampling.

After decomposing the input signal into high-frequency and low-frequency sub-bands using the above process, the resulting low-frequency sub-band can be used as an input signal, after which wavelet decomposition is performed to obtain the next level of high-frequency and low-frequency sub-bands, etc. As the progression of wavelet decomposition increases, the resolution in the frequency domain also increases.



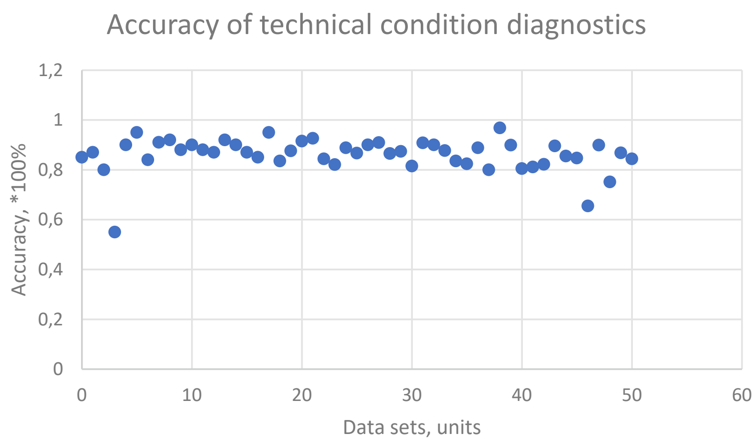
Pic. 5. Schematic diagram of a two-layer wavelet packet decomposition [26].



*Pic. 6. Performance test at 1024 * 768 pixels [performed by the authors].*

For the case of multi-signal models (Pic. 4 *c, d, e*), the discrete wavelet packet transform (DWPT) is used. It is essentially an extension and optimisation of the discrete wavelet transform (DWT). In contrast to DWT, at each level of the signal decomposition process, not only further decomposition of the low-frequency sub-band occurs, but also of the high-frequency sub-band [25]. DWPT calculates the optimal signal decomposition path by minimising the cost function that decomposes the signal transmitted in the input channel. Pic. 5 shows a two-layer wavelet packet decomposition.

So, in the process of testing the proposed ship engine diagnostic system, setting different image pixel values and setting 7 test times using a timer,



Pic. 7. Results of diagnostics of a ship engine [performed by the authors].

the system's image capture speed and frame loss rate were analysed and checked. In Pic. 6 it can be seen that with image pixels 1024 * 768 with increasing testing time difference, starting from 30 s there is loss of image data packets. At this time, the total number of collected frames is 7750, considering the number of packets lost per packet, the packet loss rate is 0,043 %. As the test time increases further, the total number of frames increases, the frame loss rate begins to decrease, and the system's maximum capture rate reaches 168 frames per second.

To further validate the actual application of the diagnostic system in the field, 50 sets of engine power curves over the past six months, including all failure modes, were obtained from the ship's microcomputer monitoring system. The diagnostic results using an adaptive wavelet neural network model and a real-time image processing platform are presented in Pic. 7.

As shown in Pic. 7, 39 sets of power curves were correctly classified as faults by the diagnostic system, and one set was scored incorrectly.

CONCLUSIONS

Summarising the results obtained, we note that to improve the accuracy of diagnostics of ship engine faults, the article proposes an approach that is based on a combination of wavelet neural network technology with multi-information image synthesis using a programmable logic circuit. Wavelet packet decomposition is a method for local time and frequency analysis. It gradually refines the signal at multiple scales through scaling and transfer operations, and it can automatically adapt to the requirements of time-frequency signal analysis, allowing us to focus on any detail of the signal.

The diagnostic results show that the efficiency of recognising breakdowns and failures of a ship engine can meet the real operational requirements of the object and be implemented.

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