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(54) **Title:** METHOD AND DEVICE FOR TESTING A MARINE TRANSMISSION

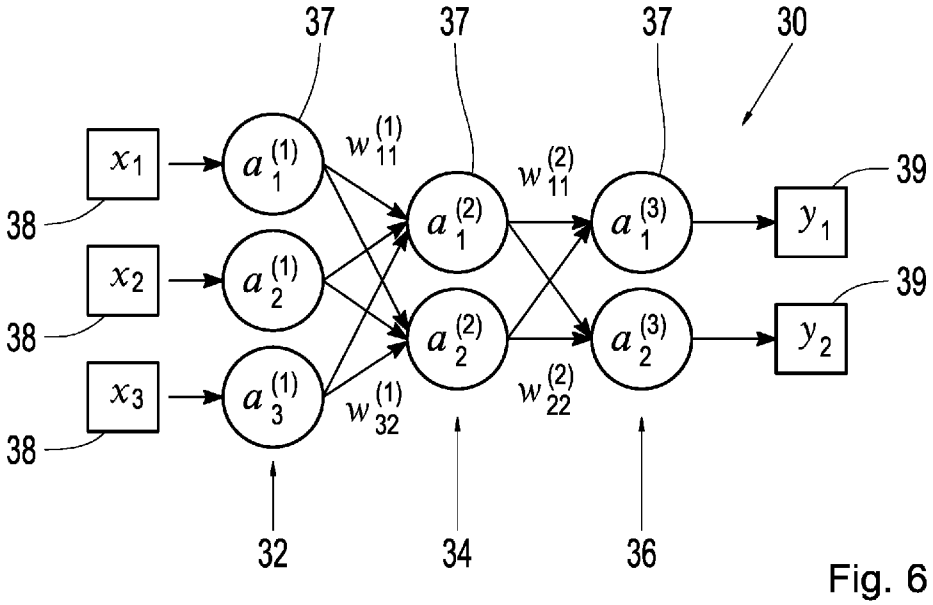


Fig. 6

(57) **Abstract:** A method for testing a marine transmission is described with transmitting an input signal to the transmission, triggering a response signal sequence of the transmission, detecting the response signal sequence by means of signal processing, processing the detected response signal sequence by means of digital image processing, wherein image data is created from the detected response signal sequence, generating at least one performance parameter of the transmission from the image data by means of a trained neural network and evaluating the at least one performance parameter using a predefined criterion. Also a device for performing the method is described.

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Method and device for testing a marine transmission

Technical field

The invention concerns a method for testing a marine transmission.

Background art

A conventional marine transmission may comprise multi disc wet clutches, a hydraulic circuit and hydraulic valves. Such a transmission may be provided with a trolling mode, at which the oil pressure of the hydraulic circuit may be controlled by means of the hydraulic valves. Controlling the valves and the clutches may affect a transmission response and may further affect the comfort on a marine vessel.

As each vessel may have a customized design, in particular a different vessel motorization or vessel weight, each marine transmission has to be adapted individually to the respective design. Thus, a standalone calibration may be needed for each vessel due to the differences in the vessel design.

Known methods and means for calibrating the control of a marine transmission aim at a desired comfort when shifting, especially in terms of smoothness and responsiveness of the transmission. A calibration of the transmission may be done by a technician before commissioning of the marine vessel. From WO 2007/081249 A1 a method of measuring coupling ratios of a marine vessel is known, wherein measurements are used for calibrating single positions of a transmission control lever that can be operated by a user for controlling the clutch engagement.

However, an important challenge remains, as the quality of a transmission calibration needs to be further subjectively evaluated since the calibrated transmission response remains sensitive to subjective impression, which cannot be directly and explicitly expressed with measurable parameters.

The claimed invention

Thus, the invention provides solutions for testing a transmission response in an efficient manner, in particular considering subjective parameters.

The method for testing a marine transmission according to the invention comprises transmitting an input signal to the transmission, triggering a response signal sequence of the transmission, detecting the response signal sequence by means of signal processing, processing the detected response signal sequence by means of digital image processing, wherein image data is created from the detected response signal sequence, providing a trained neural network for evaluating the image data, generating at least one performance parameter of the transmission from the image data by means of the neural network and evaluating the at least one performance parameter using a predefined criterion.

According to the above method, the transmission response caused by the input signal may be a time-dependent response signal. This response signal may be converted in image data, wherein the response signal may be discretised in image pixels still showing the response signal path within the image. Based on such image data, a comparison with training data also provided in image data may be conducted. An analysis of the shifting behavior of the transmission may then be evaluated with the neural network, wherein performance grades may be a test result.

Hence, the method enables a technician to evaluate the current setting of a transmission and to check whether a further reconfiguration of the transmission is necessary to improve the (subjective) behavior of the transmission.

Carrying out the test method may in particular be done before, during or after a commissioning or calibration procedure of the marine transmission.

The input signal may be provided and transmitted to the transmission by a marine control system and may be a single transmission input signal, for example a certain set speed of the output shaft of the transmission or a set speed of the propeller being connected to the output shaft.

A pre-defined test signal sequence may comprise a zero signal followed by a step signal up to a set speed of the propeller. This transmission input signal sequence may simulate a clutch-in operation being a particularly critical operation when the transmis-

sion is requested to change its state from neutral, wherein no torque may be transmitted to the output shaft, to ahead or astern gear, wherein a high or maximum torque may be transmitted to the output shaft.

The marine transmission may provide a manual or automatic gear shift for a vessel. The transmitted input signal may trigger a vessel gear shifting. For this purpose a hydraulic unit of a gear box may be controlled.

Based on the triggered shifting of the transmission, the response signal sequence (also called response signal path) may be caused. The response signal sequence may be an actual speed of the output shaft of the transmission or an actual speed of the propeller. Detecting the triggered response signal sequence may comprise measuring the response signal sequence.

Following the detection, a core idea of the invention may be seen in providing a metric for comparing an actual detected transmission response with test data of acceptable and not acceptable transmission behaviour for evaluating the quality of marine transmission shifting. Although each design of a marine transmission and the vessel in which the transmission is used may be different, an automated and intelligent test procedure can be provided for supporting a technician by automatically matching a transmission response to pre-defined acceptance criteria, which may comprise at least one soft criterion. For this purpose, the shape of the transmission response may be compared to an ideal response using a neural network based on image processing techniques.

Further, a feedback based on the evaluation with the neural network may be provided for calibrating or re-calibrating the transmission response, wherein parameters of the transmission may be newly set or adjusted. The method may further provide a test result in digital or analogous manner, based on which transmission parameters or settings may be changed automatically or manually.

In an embodiment the triggered response signal sequence comprises a speed of an output shaft of the marine transmission. The response signal sequence of the output shaft may be captured during a pre-defined time duration. Thus, a time-dependent re-

sponse signal may be sampled during a certain sample time. Accordingly, a sequence of samples may be stored as a vector. Vectorizing the signal sequence has the advantage that each vector element may be further processed individually.

In an embodiment processing the detected response signal sequence comprises creating the image data by means of fuzzy logic. Fuzzy logic may be based on many-valued logic in which a truth value may be any real number between zero and one. The image data may be created by transforming the time-dependent and one-dimensional response signal sequence into a spatial two-dimensional image using fuzzy-logic. Transforming may comprise converting the transmission response signal or the vectorized response signal sequence into image pixels. Using image processing techniques has the advantage that a shift of the response signal response that is represent within the image data may compensated by adjusting the image size to the signal data. The response signal path, which is still present within the image data, may for example be centralized, wherein a cropping of the image data may be carried out. The picture section may thus be reduced to the actual signal path.

In an embodiment the application of fuzzy logic comprises employing a fuzzy set of membership functions based on a predefined value of a target parameter of the marine transmission. Each vector element of the sample sequence may be mapped to one of a fuzzy set of membership functions. At least three membership functions based on the target parameter, for example a target propeller speed, may be defined. A membership of each vector element to one membership function may be expressed with a real number between zero and one. Membership function may be triangle membership functions and/or Gaussian membership function. Considering the signal being between zero and two times the target parameter a set of triangle membership functions may be defined, wherein the triangle membership functions may be defined on both sides of the target parameter plus/minus its own value.

Reading and converting a transmission response signal into an image may be carried out as follows: An original signal x(t), may be sampled during a sample time T, between t=0 and t=(m-1)T, wherein a sequence of m samples may be stored as {x[k]}. Each point x[k] may then be mapped to one of n fuzzy sets through fuzzy membership functions.

As example, n=3 fuzzy sets can be defined as F1 (signal is above target), F2 (signal is on target) and F3 (signal is below target). A membership of x to any fuzzy set may be expressed with a real number between 0 and 1 through a membership function. Considering the signal x being between 0 and 2 times the target, that means a range of the target plus/minus its value, a set of membership functions may be defined as may be taken from Formula 1:

$$\mu_F(x): U \rightarrow [0,1]$$

Formula 1

In case of using fuzzy sets as described above, the following triangle membership functions according to Formula 2 can be used as an example:

$$\mu_{F1}(x) = \max(0, |(x - 2 * Target)/Target|)$$

$$\mu_{F2}(x) = \max(0, |(x - Target)/Target|)$$

$$\mu_{F3}(x) = \max(0, |x/Target|)$$

Formula 2

The result may be a transformation of the fixed length signal x(t) into a n x m matrix of normalized values between 0 and 1. A larger number of fuzzy sets n can be used for a higher resolution, wherein n may be increased respectively.

An embodiment further comprises transforming each pixel of the image data into data having a value between zero and one. Hence, using the above steps, the response signal or the sample vector may be transformed from its one-dimensional data structure into a two-dimensional matrix of normalized values between zero and one. The matrix may be a greyscale image with pixel values between zero and one. Increasing the density or resolution of the image data may be achieved by increasing the matrix dimensions respectively.

An embodiment further comprises filtering the image data for reducing the image size and/or for feature extraction. Filtering image data may be performed or processed before comparing the image data by means of the neural network. The image size may be reduced by this pre-filtering step. Feature extraction may comprise enhancing a feature,

in particular the signal path or shape. Convolutional filters may for example be used. Filtering image data may also be understood as creating an image hash or footprint being calculated for data compression and reduction. Filtered image data, in particular reduced in data size, is advantageous prior to using the data in the neural network, as computational speed may be increased. Furthermore, as the neuron activations of the neural network are very sensitive to small variations, filtered image data may increase the efficiency and reliability of the performance parameters being the output of the neural network.

Image data filtering may be further done via a pooling operation. The matrix of normalized values may be split in sub-matrices. Elements of a new matrix may be calculated by taking maximum values of the sub-matrix as new matrix elements. The matrix may form a filtered image which filtered pixels. Instead of the pooling operation based on maximum value calculation also other operations like average or median functions may be used for calculating new matrix elements.

The filtered image data may then be fed into a neural network. In an embodiment the neural network, into which filtered image data may be fed, is a feedforward neural network comprising at least three layers, which comprise an input layer, at least one hidden layer and an output layer. The neural network may comprise artificial neurons as mathematical functions with inputs, input weights and outputs. The output may be connected to the input of another neuron. The neural network used may be a fully connected feedforward neural network, wherein artificial neurons may be organised in layers and all outputs of one layer may be connected to the inputs of each neuron in another layer.

An artificial neuron may be a mathematical function according to Formula 3 with I inputs x1 through xI and input weights w1 through wI. The Output of the kth neuron may be defined as:

$$y_k = \phi\left(\sum_{j=1}^{I} w_{kj} x_j\right)$$

Formula 3

Where ϕ may be the output function. Often an additional input with fixed value x0 = 1 may be added to an artificial neuron and called bias. A linear function according to Formula 4 or a logistic function according to Formula 5 may be used:

$$\phi(x) = x \quad \text{Formula 4}$$

$$\phi(x) = 1/(1 + e^{-x}) \quad \text{Formula 5}$$

A three-layered feedforward network may be used with 12 input neurons and 3 output neurons. The 12 elements hij of the hashed N x M matrix H may be connected one by one to the 12 input neurons. The input neuro can also be set to have a linear output function and to have unitary weight, thus output of kth input neuron may correspond to kth input of the network according to Formula 6:

$$h_{ij} \rightarrow x_k \qquad k = M(i-1) + j \quad \text{Formula 6}$$

A hidden layer may comprise 20 neurons with a logistic output function. Each neuron of the input layer may have 12 inputs and may get a signal from any of the input neurons. Synapses weights may be set through network training. An output layer may be made of 3 neurons with a logistic output function. Each neuron of the output layer may have 20 inputs and may get a signal from any of the hidden layer neurons. Synapses weights may be set through network training.

A training data used for training the neural network may be based on artificial data or real data. Training and back propagation of the neural network may be carried out in conventional manner.

An embodiment further comprises providing a matching score based on the at least one performance parameter output by the neural network for evaluating the at least one performance parameter. A performance parameter may be evaluated as TRUE or FALSE,

wherein in case the performance parameter is TRUE, for example a value of one may be assumed. Also graded values depending on a degree of truthiness may also be calculated. The result of adding up all evaluation values may be the matching score based on which an evaluation of the shifting quality of the marine transmission may be carried out.

The invention may comprise a network with 3 outputs, which can be defined as the degree of truthiness of the following sentences, expressed between 0 and 1, where 0 may mean the sentence is FALSE and 1 may mean the sentence is TRUE: y1 (transmission response is good), y2 (transmission response is slow) and y3 (transmission response is too aggressive).

The neural network system may to be trained to classify the inputs correctly. The process of training may comprise determining the weights on the hidden and output layers that may yield the desired results. This may be achieved by feeding the system with a set of known inputs, the learning or training set, and then tuning the weights in order to achieve the desired outputs.

For quantifying how well the system is achieving its goal a cost function may be defined according to Formula 7 such as for example the cross-entropy

$$C(x,w) = \sum_{x} \|y(x,w) - t(x)\|^2$$ Formula 7

where x may be a training input, t(x) may be the desired output, y(x,w) may be the actual output. Good performances may be achieved when the cost function C(x,w) is minimized and hence the problem of training the weights becomes an optimization problem. Such optimization problems can usually be solved iteratively using gradient-based methods. At each iteration of the method, the vector of weights may be updated according to Formula 8:

$$\Delta w_{ij} = -\eta \frac{\partial C}{\partial w_{ij}}$$

Formula 8

This applies for every weight, that means synapsis, wherein η may be a tuneable parameter that may be a learning rate. Hence, training the network may be the process of iteratively minimizing the cost function until the results are considered sufficiently close to the desired outputs. Different cost functions, for example the cross-entropy, can be chosen to improve the efficiency of the learning process and different known methods to initialize the weights may be used.

To choose the training set and the architecture of the network correctly, different strategies can be used to improve a test error, that means the error on a set of inputs different from the training set. This is known as regularization. An example of regularization may be to include the L2 norm of the weight vector in the cost function.

The network may be trained for properly interpreting any significant input neuron. Extreme reduction of network input to a 3 x 4 elements H matrix may allow to compose a small training set. Representation of the inputs as a small image may allow for visualizing the training set.

A second batch of element of the training set may be proposed to increase the capability of the network for identifying similarities when processing actual inputs. In the feed-forward network the neuron inputs may have a flat structure. That means there may be no spatial relationship between the neurons visualizing them as an image. In the network, two neurons mapping two adjacent elements of the H matrix may be just two different inputs and may have no relationship between them. A selection of the first batch can produce an aliasing issue due to sharp edges inputs. A training set may build a spatial relationship between neighbours and this may be done by creating a second batch of training elements created with contamination of adjacent elements of the H matrix. Contamination on proximity may be realized in the following way: Each active neuron (activation = 1) may produce a 0.1 increment of activation on each adjacent inactive neuron (original activation = 0) and decreases its own activation by 0.1.

A different number of layers and a different size of each layer of the network can be chosen. A reduced number of input layers may allow to avoid an overfitting of the network. Tailoring of the network comprises the ability of identifying training input but flexibility is lost when an actual input which is not perfectly fitting a training sample is provided. If many input neurons are present, the training set may be large enough to educate any neuron to respond properly, otherwise the network may respond to training set but response to inputs which are not in the training set would be unpredictable.

An embodiment further comprises generating three performance parameters by means of the neural network for evaluating a transmission response, wherein a first performance parameter describes the quality of the transmission response, a second performance parameter describes the speed of the transmission response and a third performance parameter describes the aggressiveness of the transmission response. When evaluating the calibration of the transmission, a trade-off between quick and smooth transitions may be found, wherein such a trade-off cannot be directly mathematically defined as it is rather a soft requirement or soft parameter. The quality of the transmission response performance parameters may thus be simply evaluated with soft criteria. However, sophisticated physical values may optionally be used. The speed of the transmission response may be of particular interest, when the transmission operation is accomplished with a joystick interface operated by a user.

Ratings can be translated to an acceptance criterion. In this case transmission a response may be acceptable if first output y1 is above a first predefined threshold and both second and third output y2 and y3 are below respectively a second and third threshold. The ratings can also be associated to a compliancy level in the form of percentage between 0% and 100%.

An embodiment further comprises evaluating the at least one performance parameter by comparing the at least one performance parameter with a predefined threshold value. The output of the neural network may lead to any value between zero and one, which may be a rating of the transmission response. For each performance parameter, a threshold may be defined. A first threshold may be defined for the first performance

parameter describing the quality of the transmission response, wherein the transmission response may be acceptable if the parameter is above the threshold, that means good enough. A second threshold may be defined for the second performance parameter describing the speed of the transmission response, wherein the transmission response may be acceptable if the parameter is below the threshold, the means fast or quick enough. A third threshold may be defined for the third performance parameter describing the aggressiveness of the transmission response, wherein transmission response may be acceptable if the parameter is below the threshold, that means efficient or aggressive enough. Ratings may also be associated with a compliancy level that means evaluated in certain percentage values.

In an embodiment the neural network may be a convolutional neural network. A convolutional neural network is a special class of a feedforward artificial neural network, wherein characteristics of space or time shift invariance may be added. The convolutional neural network may comprise an input layer, at least one hidden layers and an output layer, wherein the at least one hidden layer may comprise convolutional and/or pooling layers. The response signal sequence converted into the n to m matrix by means of fuzzification may be fed into the convolutional neural network.. Hereto a convolutional layer and/or a pooling layer may be used, wherein pre-designed convolutional kernels may be applied for pre-processing the response signal sequence.

Convolutional layers of the convolutional neural network apply a convolution operation to the input matrix using a smaller convolutional matrix. By using the convolutional layer specific features present in the input matrix may be extracted or enhanced. The input matrix can be treated with several convolutional matrices, producing an output matrix of the same size of input matrix for each convolution. More formally, if the input matrix may be in the n x m form and C convolutional matrices may be provided, output of convolutional layer is n x m x C. Convolutional matrices in a Convolutional neural network may be determined through training and backpropagation. To reduce computation and training effort, more common pre-engineered convolutional kernels can be used, known from image processing.

A pooling layer in a convolutional neural network has the function of combining the outputs of neuron clusters at one layer into a single neuron in the next layer. More generally, a pooling layer can be used to treat the output of a convolutional layer in order to reduce the size of the data to be processed to the next layers. As an example, a pooling layer can reduce the n x m x C output of a convolutional layer into a N x M x C output with $N < n$ and $M < m$. Several sequences of convolution-pooling can be applied to the original input until the data is small enough to be connected as input of a fully connected feedforward network.

An embodiment further comprises matching of the response signal sequence, the image data and/or the at least one performance parameter to a known response profile. For this purpose, a list of response profiles may be provided, wherein the response signal sequence may be matched to these profiles. Thus, a comparison to a known or already evaluated transmission behaviour of another marine transmission may be provided. The output neurons of the neural network may identify different transmission response profiles and rate an actual transmission response with its similarity to one archetype of the response profiles.

A test device according to the invention is configured to perform the method according to the invention. The device may be configured for measuring a transmission response signal, for example an output shaft speed, and for processing and analysing the transmission response signal. The test device may be a commissioning tool for commissioning of a marine vessel. An automatic tool for an automatic test of the marine transmission may thus be provided. The test device may be further configured as a calibration device for calibrating a marine control system for controlling the transmission.

The method for testing a marine transmission, its steps and its embodiments are subsequently further described with respect to the schematic Figures 1 to 10.

Brief description of the figures

Fig. 1 shows single steps of the method for testing a marine transmission.

Fig. 2a shows a first membership function of a fuzzy set of membership functions.

Fig. 2b shows a second membership function of a fuzzy set of membership functions.

Fig. 2c shows a third membership function of a fuzzy set of membership functions.

Fig. 3 shows a transformation from a response signal sequence to an image.

Fig. 4 shows a transformation from the response signal sequence to an image with higher resolution than the image in Fig. 3.

Fig. 5 shows filtered image data.

Fig. 6 shows inputs, neurons and outputs of a neural network.

Fig. 7 shows layers of the neural network.

Fig. 8 shows a first batch of elements of a training set and target outputs.

Fig. 9 shows a second batch of elements of a training set and target outputs.

Fig. 10 shows a response of a trained neural network.

Detailed description

Figure 1 shows the steps of the method for testing a marine transmission. In a first step 100, an input signal is transmitted to the transmission, wherein a set propeller speed as a step signal is transmitted. In a second step 110, a response signal sequence 10 of the transmission is triggered, wherein a shifting of the transmission causes an actual propeller speed as signal sequence which deviates from the ideal set propeller speed signal. At a third step 120, the response signal sequence 10 is detected by means of signal processing. The signal processing provides a time-dependent signal path based on the

response signal sequence 10. At a fourth step 130, the detected response signal sequence 10 is processed by means of digital image processing. Digital image processing provides a transformation of the time-dependent signal path into a two-dimensional image of the path being converted in a greyscale pixel matrix.

Within step 130 sub-steps 132, 134, 136 are carried out. At sub-step 132, membership functions 51, 52, 53 are applied on the response signal sequence 10, wherein the response signal sequence is vectorized and each vector element is allocated to one of the membership functions 51, 52, 53. At sub-step 134, image data 20 is created from the response signal sequence 10 by means of fuzzy logic. At sub-step 136, the image data 20 is filtered, wherein the image resolution is decreased by an average, median or Gaussian filter.

At a fifth step 140, the image data 20 is fed to a trained neural network 30 for evaluating the image data 20. At a sixth step 150, three performance parameters 41, 42, 43 of the transmission are generated from the image data 20 by means of the neural network 30. At a seventh step 160, the three performance parameters 41, 42, 43 are evaluated using a predefined criterion.

Figures 2a to 2c show membership functions 51, 52, 53 as employed in sub-step 132. A first membership function 51, a second membership function 52 and a third membership function 53 of a fuzzy set of membership functions 51, 52, 53 are shown. The first membership function 51 provides a functional value greater than zero when the response signal sequence 10 is below a target parameter 50 with its functional maximum at zero target parameter 55. The second membership function 52 provides a functional value greater than zero when the response signal sequence 10 is on the target parameter 50 with its functional maximum at single target parameter 50. The third membership function 53 provides a functional value greater than zero when the response signal sequence 10 is above the target parameter 50 with its functional maximum at double target parameter 54. Membership functions 51, 52, 53 are formed as respective complete or partly triangle functions. The abscissa of Figures 2a to 2c concerns target parameters of the marine transmission, wherein the zero target parameter 55, the single target pa-

rameter 50 and the double target parameter 54 are respective points of interest. The ordinate of Figures 2a to 2c concerns normalized values between 0 and 1.

Figures 3 and 4 show on the left the response signal sequence 10 as triggered in step 110 and detected in step 120. The abscissa of Figures 3 and 4 concerns time. The response signal sequence 10 may be triggered by an input step-signal of a set propeller speed input to a transmission controller in step 100, wherein the step-signal comprises a zero-signal followed by a step to a set target value, for example a set speed of the propeller. The ordinate of Figures 3 and 4 concerns the response signal itself, for example a measured propeller speed.

Figures 3 and 4 further show on the right image data 20 with pixels 21 as created in sub-step 134. The greyscale image data 20 in Figure 3 results from a transformation of the response signal sequence on the left by means of the three membership functions 51, 52, 53 of Figures 2a to 2c, wherein membership function 51 is applied in the lower row of the image data 20, membership function 52 is applied in the middle row of the image data 20 and membership function 53 is applied in the upper row of the image data 20. The image data 20 in Figure 4 results from a transformation of the response signal sequence on the left by means of a wider set of membership functions (not shown), for example eleven functions.

Fig. 5 shows a reduced three to four-dimensional matrix of filtered image data 22 as created in sub-step 136. Each filtered pixel 23 is calculated based on a sub-matrix of pixels 21 in image data 20. Filtered pixels 23 may be calculated by an average function.

Fig. 6 shows an architecture of the neural network 30 used in step 150. The neural network 30 comprises an input layer 32, a hidden layer 34 and an output layer 36. Each layer 32, 34, 36 comprises a respective number of neurons 37, wherein a previous neuron is connected with each neuron of the following layer. Filtered pixels 23 are network inputs 38 and performance parameters 41, 42, 43 as generated in step 150 are network outputs 39.

Figure 7 shows an exemplary architecture of the neural network 30 as provided in step 140, with twelve neurons 37 in the input layer 32, at least two neurons 37 in the hidden layer 34 and three neurons 37 in the output layer 36 corresponding to the performance parameters 41, 42, 43. The number of the input neurons 37 generally corresponds to the number of filtered pixels 23 within the filtered image data 22. Generally, the number of neurons 37 of the hidden layer 34 is greater than the number of neurons 37 in the input layer 32.

Figure 8 shows on the left a first exemplary batch of elements of a training set in matrices 1) to 7). The training sets are used for training the neural network 30, wherein each training set may be based on a preceding vessel testing or may be based on artificial data. Further in Fig. 8, exemplary target outputs t = t1 ... t3, with reference to network outputs y = y1 ... y3 are shown on the right. These outputs correspond to a first performance parameter 41 describing the quality of the transmission response as good (value 1) or bad (value 0), a second performance parameter 42 describing the speed of the transmission response as slow (value 1) or fast enough or quick (value 0) or and a third performance parameter 43 describing the aggressiveness of the transmission response as too aggressive (value 1) or suitably aggressive (value 0).

Figure 9 shows on the left a second exemplary batch of elements of a training set in matrices 1) to 7) together with target outputs on the right according to a 0.1 incrementation of activation.

Figure 10 shows an exemplary response of a trained network. The first input results in a positive evaluation of the network, since the first output concerning the transmission response is at 1 (good response), the second output concerning the speed of the transmission is at 0 (quick response) and the third output is at 0 (suitable aggressiveness). Second input determines a positive evaluation of the network, but highlights, since the first output is at 1, the second output is at 0, and the third output is rather at 0.5.

Hence, using signal processing techniques for detecting the response signal sequence 10 of a marine transmission with image processing techniques applied together

with a neural network 30 provides an efficient way of evaluating soft performance parameters 41, 42, 43 of a transmission response.

List of reference signs

10 response signal sequence

20 image data

21 pixel

22 filtered image data

23 filtered pixel

30 neural network

31 feedforward neural network

32 input layer

34 hidden layer

36 output layer

37 neuron

38 network input

39 network output

41 first performance parameter

42 second performance parameter

43 third performance parameter

50 target parameter

51 first membership function

52 second membership function

53 third membership function

54 double target parameter

55 zero target parameter

100 transmitting input signal

110 triggering response signal

120 detecting response signal

130 processing response signal

132 employing membership functions

134 creating image data with fuzzy logic

136 filtering image data

140 providing trained neural network

150 generating performance parameter

160 evaluating performance parameter

162 providing matching score

164 comparing with threshold

Claims

1. Method for testing a marine transmission,
comprising the steps of:
transmitting (100) an input signal to the transmission,
detecting (120) a response signal sequence (10) by means of signal processing,
processing (130) the detected response signal sequence (10) by means of digital image processing, wherein image data (20) is created from the detected response signal sequence (10),
generating (150) at least one performance parameter (41, 42, 43) of the transmission from the image data (20) by means of a trained neural network (30) and
evaluating (160) the at least one performance parameter (41, 42, 43) using a predefined criterion.

2. Method according to claim 1,
wherein the response signal sequence (10) comprises a speed of an output shaft of the marine transmission.

3. Method according to claim 1 or 2,
wherein the step of processing (130) the detected response signal sequence (10) comprises a sub-step of creating (132) the image data (20) by means of fuzzy logic.

4. Method according to claim 3,
wherein the application of fuzzy logic comprises employing (134) a fuzzy set of membership functions (51, 52, 53) based on a predefined value of a target parameter (50) of the marine transmission.

5. Method according to one of the preceding claims, further comprising
transforming each pixel (21) of the image data (20) into data comprising a value between 0 and 1.

6. Method according to one of the preceding claims, further comprising

filtering (136) the image data (20) for reducing the image size and/or for feature extraction.

7. Method according to one of the preceding claims,
wherein the neural network (30) is a feedforward neural network (31) comprising at least three layers (32, 34, 36), which comprise an input layer (32), at least one hidden layer (34) and an output layer (36).

8. Method according to one of the preceding claims, further comprising
providing (162) a matching score based on the at least one performance parameter (41, 42, 43) for evaluating (160) the at least one performance parameter (41, 42, 43).

9. Method according to one of the preceding claims, further comprising
generating (150) three performance parameters (41, 42, 43) by means of the neural network (20) for evaluating a transmission response, wherein
a first performance parameter (41) describes the quality of the transmission response,
a second performance parameter (42) describes the speed of the transmission response and
a third performance parameter (43) describes the aggressiveness of the transmission response.

10. Method according to one of the preceding claims, further comprising
evaluating (160) the at least one performance parameter (41, 42, 43) by comparing (164) the at least one performance parameter (41, 42, 43) with a predefined threshold value.

11. Method according to one of the preceding claims,
wherein the neural network (30) is a Convolutional neural network.

12. Method according to one of the preceding claims, further comprising
matching of the response signal sequence (10), the image data (20) and/or the at least one performance parameter (41, 42, 43) to a known response profile.

13. Test device that is configured to perform a method according to one of the preceding claims.

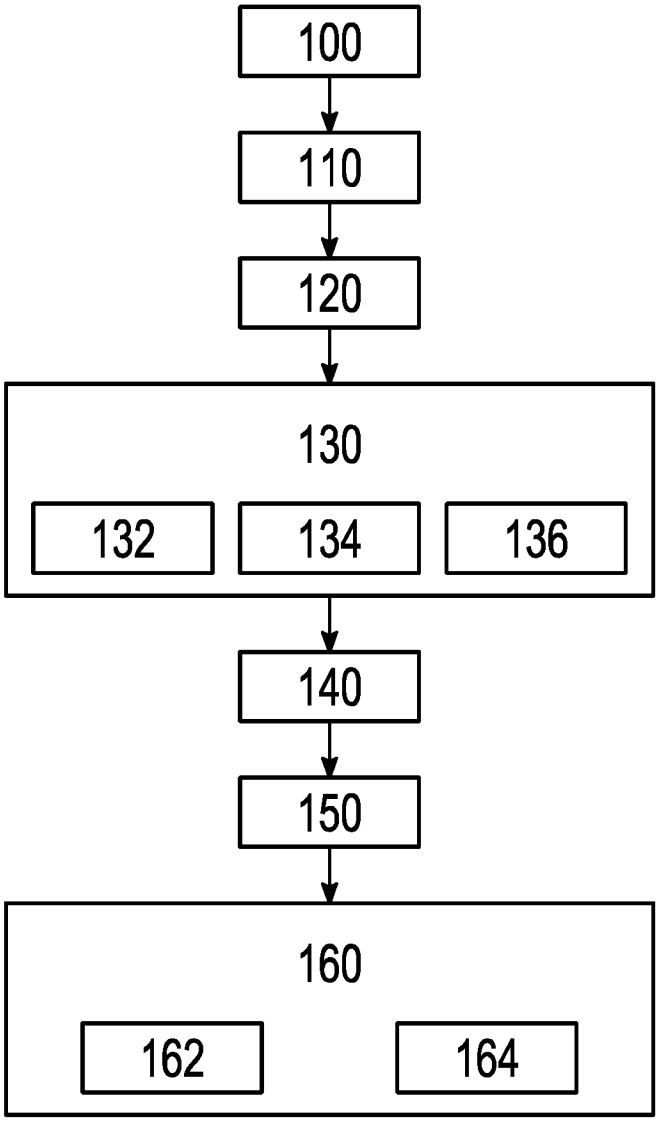


Fig. 1

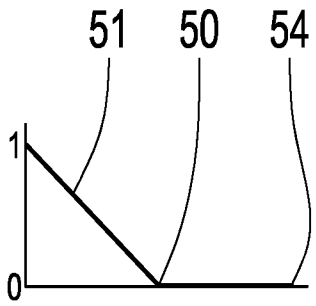


Fig. 2a

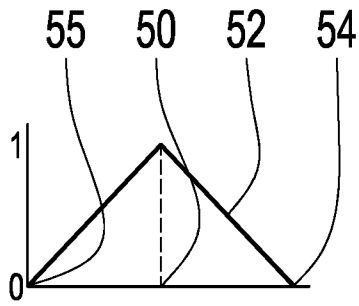


Fig. 2b

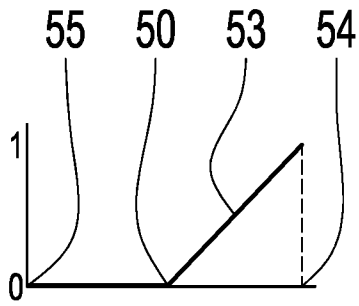


Fig. 2c

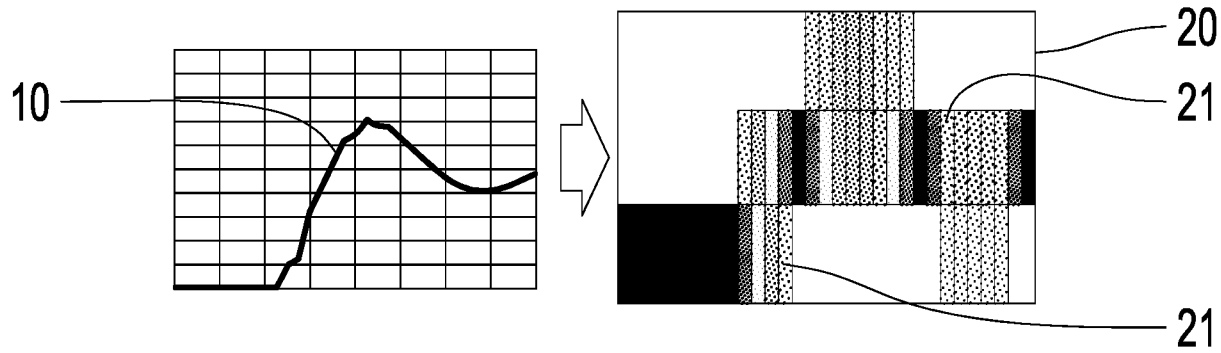


Fig. 3

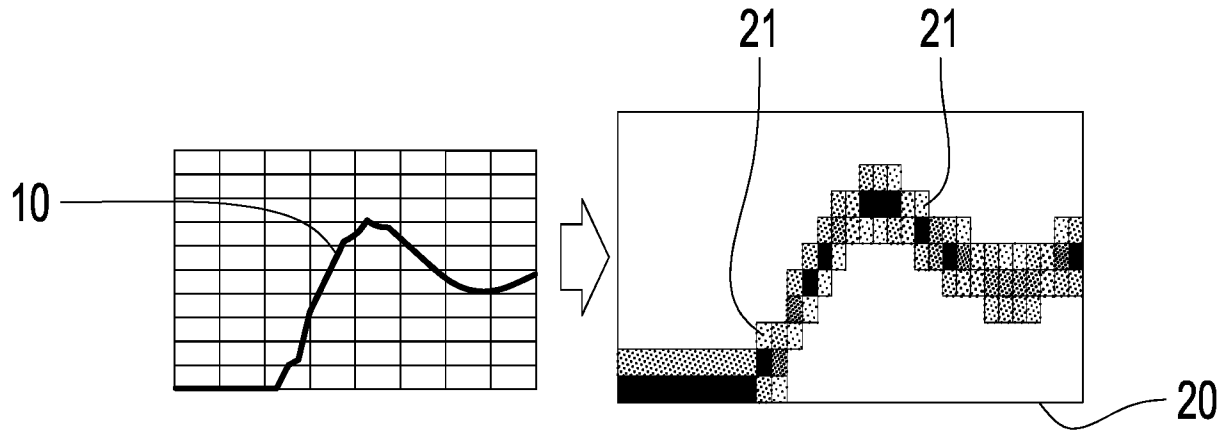


Fig. 4

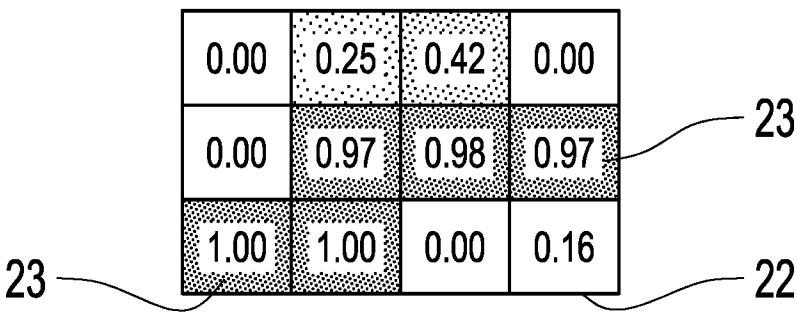


Fig. 5

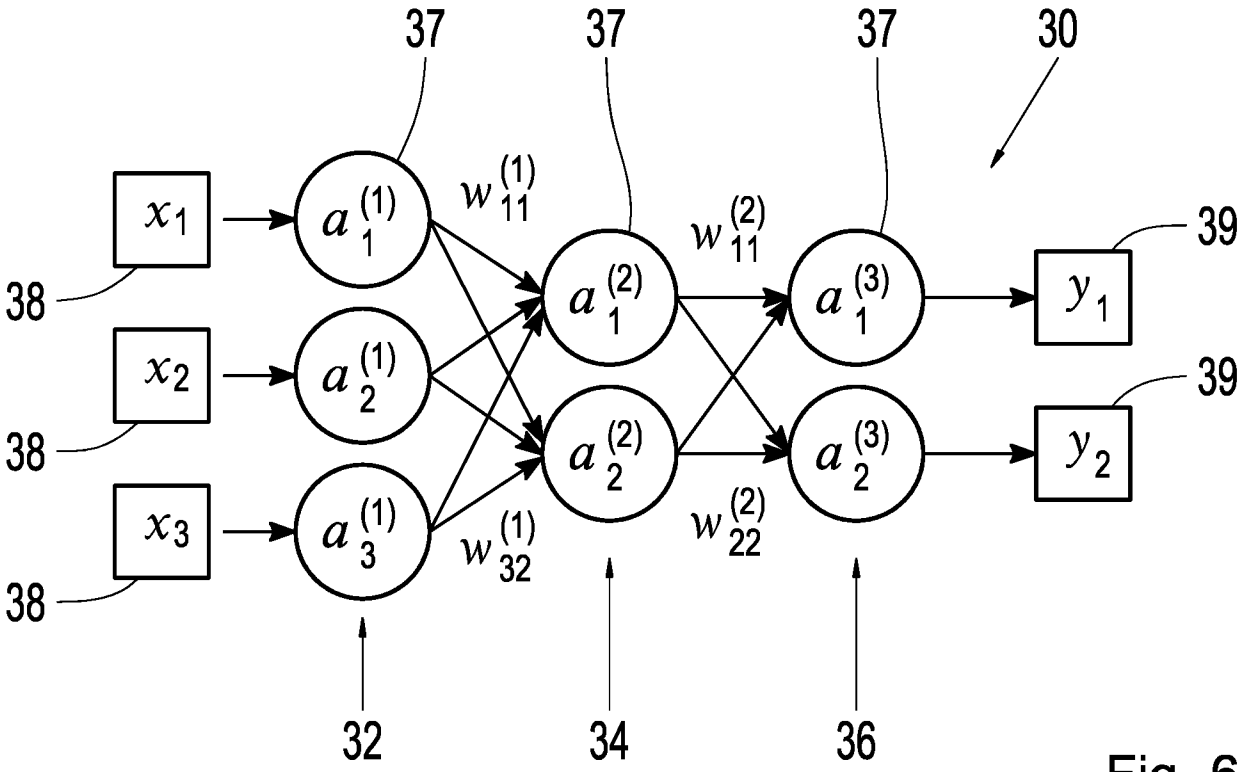

37
37
37
30
x_1
x_2
x_3
$a_1^{(1)}$
$a_2^{(1)}$
$a_3^{(1)}$
$w_{11}^{(1)}$
$w_{32}^{(1)}$
$a_1^{(2)}$
$a_2^{(2)}$
$w_{11}^{(2)}$
$w_{22}^{(2)}$
$a_1^{(3)}$
$a_2^{(3)}$
y_1
y_2
39
39
38
38
38
32
34
36

Fig. 6

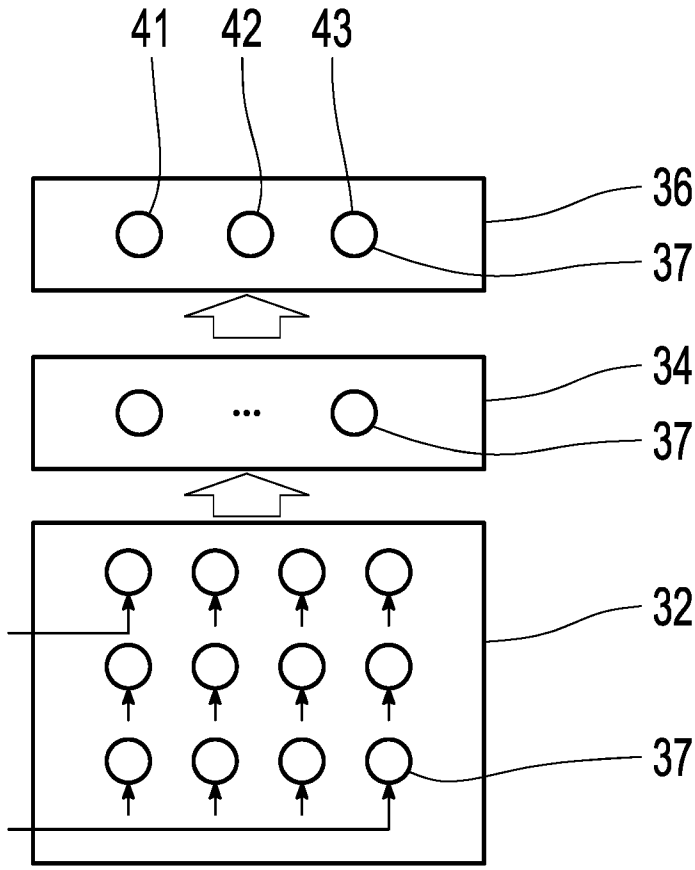

41
42
43
36
37
34
37
32
37

Fig. 7

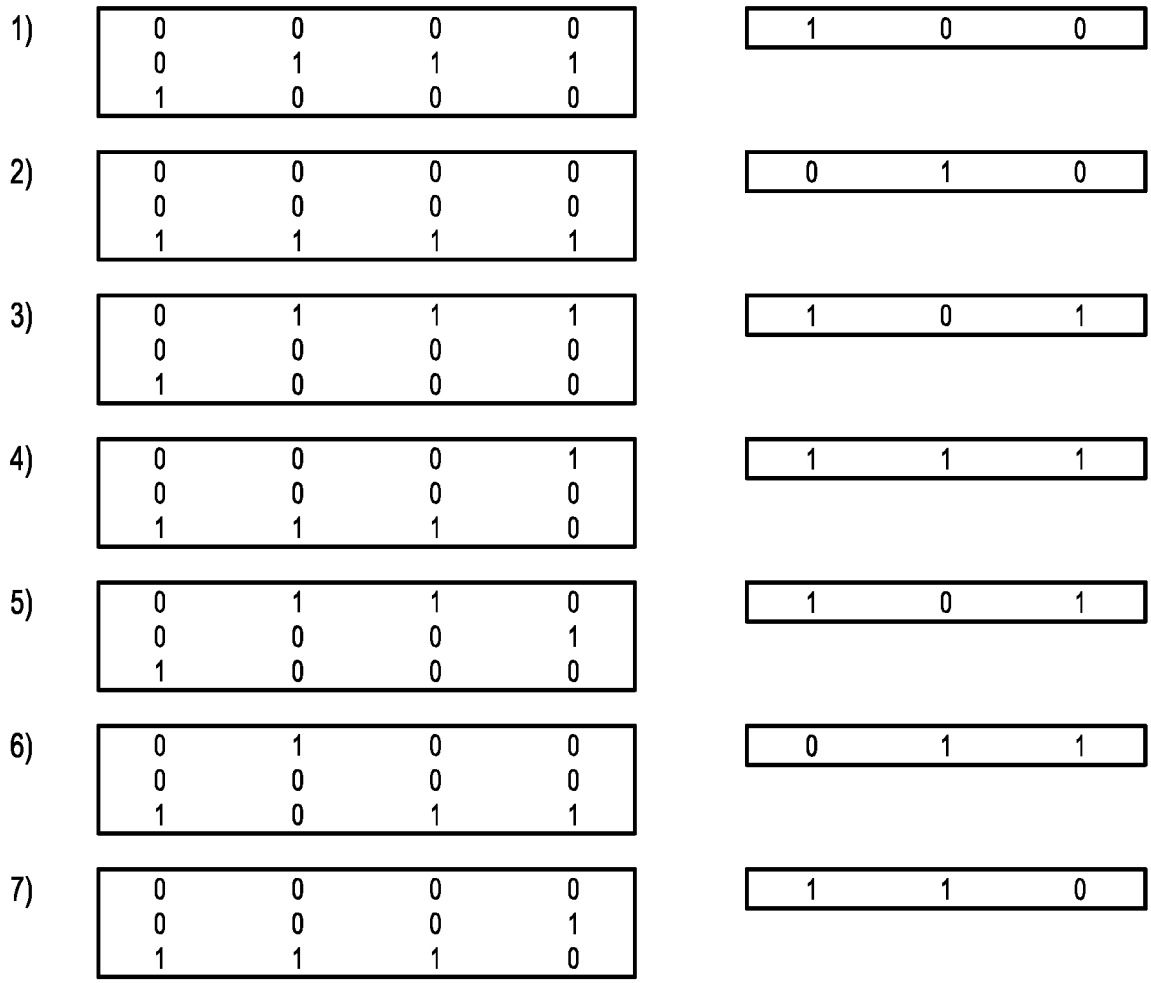

1)
0 0 0 0
0 1 1 1
1 0 0 0
1 0 0
2)
0 0 0 0
0 0 0 0
1 1 1 1
0 1 0
3)
0 1 1 1
0 0 0 0
1 0 0 0
1 0 1
4)
0 0 0 1
0 0 0 0
1 1 1 0
1 1 1
5)
0 1 1 0
0 0 0 1
1 0 0 0
1 0 1
6)
0 1 0 0
0 0 0 0
1 0 1 1
0 1 1
7)
0 0 0 0
0 0 0 1
1 1 1 0
1 1 0

Fig. 8

1)	0	0.1	0.1	0.1	1	0	0
	0.1	0.8	0.8	0.8			
	0.9	0.1	0.1	0.1			
2)	0	0	0	0	0	1	0
	0.1	0.1	0.1	0.1			
	0.9	0.9	0.9	0.9			
3)	0.1	0.9	0.9	0.9	1	0	1
	0.1	0.1	0.1	0.1			
	0.9	0.1	0	0			
4)	0	0	0.1	0.9	1	1	1
	0.1	0.1	0.1	0.1			
	0.9	0.9	0.9	0.1			
5)	0.1	0.9	0.9	0.1	1	0	1
	0.1	0.1	0.1	0.8			
	0.9	0	0	0.1			
6)	0.1	0.9	0.1	0	0	1	1
	0.1	0.1	0.1	0.1			
	0.9	0.1	0.9	0.9			
7)	0	0	0	0.1	1	1	0
	0.1	0.1	0.1	0.8			
	0.9	0.9	0.9	0.1			

Fig. 9

1)	0.1	0	0.2	0.1	1	0	0
	0	0.3	0.7	0.8			
	0.9	0.7	0.1	0.1			
2)	0.1	0	0.8	0.6	1	0	0.5
	0	0.3	0.2	0.4			
	0.9	0.7	0	0			

Fig. 10

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2019/052807

A. CLASSIFICATION OF SUBJECT MATTER
INV. B63H23/00 B63B9/00 G06F17/00 G06N3/02
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
B63H B63B G06F G06N

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	CN 106 697 187 A (UNIV WUHAN TECH) 24 May 2017 (2017-05-24)	1,2, 8-10,12, 13
Y	figures 1-5 paragraphs [0003] - [0004] claim 6	3-7,11

Y	US 5 606 646 A (KHAN EMDADUR R [US] ET AL) 25 February 1997 (1997-02-25) abstract column 16, lines 18-38	3,4,7

Y	US 2017/103309 A1 (CHANG LELAND [US] ET AL) 13 April 2017 (2017-04-13) abstract paragraph [0022]	5,6,11

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[X] Further documents are listed in the continuation of Box C.

[X] See patent family annex.

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"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
2 April 2019	10/04/2019

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Freire Gomez, Jon

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INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2019/052807

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	WO 2007/081249 A1 (VOLVO PENTA AB [SE]; LOODBERG PAAL [SE]; BROBERG MARCUS [SE]) 19 July 2007 (2007-07-19) cited in the application the whole document -----	1-13

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/EP2019/052807

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