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NOTICE

The above identified patent application is available for licensing. Requests for information should be addressed to:

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1	Navy Case No. 77849
2	SYSTEM FOR BEARINGS-ONLY CONTACT STATE
3	ESTIMATION USING RECURRENT NEURAL NETWORKS
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5	STATEMENT OF GOVERNMENT INTEREST
6	The invention described herein may be manufactured by or for
7	the Government of the United States of America for Governmental
8	purposes without the payment of any royalties thereon or
9	therefor.
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11	BACKGROUND OF THE INVENTION
12	(1) Field of the Invention
13	The invention relates generally to the field of estimation
14	and tracking, and more particularly to systems and methods for
15	bearings-only contact state estimation and target motion analysis
16	for marine applications.
17	(2) Description of the Prior Art
18	In the ocean environment, localization and tracking of an
19	acoustic contact from sonar measurements are of considerable
20	interest. The two-dimensional contact state estimation, or
21	target motion analysis, problem captures the fundamental
22	essentials of tracking. Here a moving observer ("ownship")
23	monitors sonar bearings from an acoustic contact ("target")
24	assumed to have constant velocity, ane processes those
25	measurements to estimate contact location and velocity.

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1 A fundamental property of a bearings-only target motion analysis is that the process is not completely observable for any 2 3 single leg of ownship motion. This is clear from the fact that several target trajectories will generate the same bearing-4 measurement history for a constant velocity observer. The range 5 6 to the target becomes observable only following a maneuver by the 7 Several estimation techniques have been applied to the observer. bearings-only target motion analysis, with varying results. 8 The differences in methods involve the modeling of the process and 9 the selection of the estimation algorithm. The extended Kalman 10 11 filter ("EKF") in a Cartesian state-space exhibits divergence 12 problems which yield poor estimates with optimistic uncertainties. The pseudo-linear estimation technique is known 13 14 to produce biased solutions with optimistic covariances; depending on the scenario geometry, the bias can be severe. The 15 16 maximum likelihood estimator ("MLE") is one of the present techniques of choice, but it is sensitive to the initialization. 17 A two-stage hierarchical estimation approach has been proposed, 18 19 but this and the other methods are based on linear filtering and 20 estimation techniques and are approximations to the complex nonlinear nature of the real-world problem. 21

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SUMMARY OF THE INVENTION

It is therefore an object of the invention to provide a new and improved system and method for bearings-only contact state estimation and target motion analysis for marine applications.

In brief summary, in one aspect the invention provides a 1 system for bearings-only contact state estimation in response to 2 target bearing and ownship speed and course (i.e., velocity) 3 information provided for a plurality of observation legs at 4 successive points in time, including a plurality of neural 5 networks and a data fusion circuit. Each of the neural networks 6 generates range-normalized parameter estimate information for one 7 of the observation legs in response to target bearing and ownship 8 9 course information for an associated one of the observation legs, provided thereto at each point in time and information generated 10 for the previous point in time. The data fusion circuit receives 11 12 the range-normalized parameter estimate information from the 13 neural networks and generates the contact state estimation in 14 response thereto.

In a further aspect, the invention provides a neural network 15 16 neural networks for generating range-normalized parameter 17 estimate information for one of the observation legs in response to target bearing and ownship speed and course information for an 18 associated one of the observation legs, provided thereto at each 19 point in time and information generated for the previous point in 20 The neural network includes an input layer, a hidden layer 21 time. 22 and an output layer. The input layer comprises a plurality of 23 input nodes, at least some of the input nodes receiving the 24 bearing information and the ownship speed and course information for the respective one of the observation legs, at least others 25 26 of the input nodes receiving the delayed state information. The

hidden laver comprises a plurality of hidden nodes, for receiving 1 2 the bearing information, the ownship speed and course information and the delayed state information from the input nodes and 3 processing it in response to a weight information associated with 4 each input node and respective hidden node in relation to a 5 predetermined non-linear function to generate contact state 6 7 The contact state information generated at each information. point in time comprises the delayed state information for a 8 subsquent point in time. The output layer comprises a plurality 9 10 of output nodes for generating the range-normalized parameter estimate information in relation to the contact state information 11 12 generated by the hidden layer at each point in time.

BRIEF DESCRIPTION OF THE DRAWINGS

15 This invention is pointed out with particularity in the 16 appended claims. The above and further advantages of this 17 invention may be better understood by referring to the following 18 description taken in conjunction with the accompanying drawings, 19 in which:

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FIG. 1 is a functional block diagram of a system for contact
 state estimation which incorporates recurrent neural networks
 constructed in accordance with the invention; and

FIGS. 2 and 3 are functional block diagrams of neural
networks useful in the system depicted in FIG. 1.

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DESCRIPTION OF THE PREFERRED EMBODIMENT

FIG. 1 is a functional block diagram of a system 10 for 2 generating a contact state estimate which incorporates recurrent 3 neural networks. With reference to FIG. 1, the system 10 4 generates a contact state estimate using includes two primary 5 levels of subsystems, including a first level comprising neural 6 networks 11(1) and 11(2), and a second level comprising a data 7 fusion system 12. Each of the neural networks 11(1) and 11(2) 8 receive bearing measurements and ownship kinematic information 9 concerning the speed and course of the observer ship during one 10 of the observation legs required to facilitate generation of a 11 target state estimate, and generates range-normalized parameter 12 estimates which are provided to the data fusion system 12. The 13 data fusion system, in turn, receives the range-normalized 14 estimates for the respective observation legs and uses that 15 information, along with additional scenario information, to 16 generate a contact state estimate for the target. Operations 17 performed by the data fusion system in generating a contact state 18 estimate for a target in response to the range-normalized 19 parameter estimates provided by the neural networks 11(1) and 20 21 11(2) are conventional, and will not be described herein.

As noted above, each of the neural networks 11(1) and 11(2) generates range-normalized parameter estimates in response to bearing measurements and ownship kinematic information (including speed and course information, that is, ship velocity) received during a respective one of a series of observation legs (1) and

In addition, the neural network 11(2), which generates the 1 (2). 2 range-normalized parameter estimate for the second observation leg (2), receives initialization information generated by the 3 4 neural network 11(1) for the first observation leg (1), which it 5 uses in generating the range-normalized parameter estimate for observation leg (2). The structure and operation of the neural 6 7 networks 11(1) and 11(2) will be described in connection with 8 FIGs. 2 and 3, respectively.

With reference to FIG. 2, neural network 11(1), which 9 10 generates the range-normalized parameter estimate for observation 11 leg (1), comprises a plurality of nodes organized in an input 12 layer, one hidden layer, and an output layer. The nodes comprising the input layer, comprising nodes 20(1) through 20(8) 13 14 (generally identified by reference numeral 20(i)) iteratively 15 receive the bearing and ownship kinematic information, identified 16 FIG. 2 as BEARING IN, SPEED IN, and COURSE IN inputs, at 17 individual nodes 20(1) through 20(3). The BEARING IN input 18 corresponds to the "Bearing Measurements (Leg 1)" input to the 19 neural network 11(1) in FIG. 1, and the SPEED IN and COURSE IN 20 inputs correspond to the "Ownship Kinematics (Leg 1)" input to 21 the neural network 11(1) in FIG. 1.

The input information is provided to the nodes 20(i) The input information is provided to the nodes 20(i) comprising the input layer at a plurality of successive points in time t_n during the first observation leg (1). At each point in time t_n , context information, representing information generated by the nodes 21(1) through 21(5) (generally identified by

1 reference numeral 21(h)) at the previous point in time t_{n-1} is 2 coupled to the other nodes 20(4) through 20(8) of the input 3 layer. The context information is coupled through a delay 4 element, which may comprise, for example, a register, which 5 stores the information generated by the hidden layer nodes 21(h) 6 at each point in time t_n and provides it to the input layer for 7 the subsequent point in time t_{n+1} .

The nodes 20(i) comprising the input layer are connected to 8 the nodes 21(h) comprising the hidden layer through a plurality 9 of links 22(i)(h). The nodes 21(h) are all connected to a 10 plurality of output nodes 23(1) through 23(3) (generally 11 identified by reference numeral 23(0)) through a plurality of 12 links 24(h)(o). The nodes 23(o) generate respective a BEARING 13 OUT, BEARING RATE OUT and NORM RANGE-RATE OUT (normalized range-14 rate out) value, which comprise the range-normalized parameter 15 estimates (leg 1) shown as being generated by the neural network 16 17 11(1) in FIG. 1.

The neural network 11(1) generates the BEARING OUT, BEARING 18 RATE OUT and NORM RANGE-RATE OUT (normalized range-rate out) 19 value from the inputs and context information as follows. If, at 20 time t_n , B_{in} represents the bearing in value, V_n represents the 21 22 (assumed to be constant) ownship speed in value, and C_n represents the (also assumed to be constant) course in value, 23 input state vector $u_n = [B_{in} V_n C_n]^T$ (where "T" represents the vector 24 transpose operation), then the output state vector generated by 25 the hidden output nodes 21(h) is $x_n = g(W_{11}u_n + W_{12}x_{n-1})$, where $W_1 = [W_{11} W_{12}]$ 26

1 is the matrix of weights for the links and the function "g" is 2 selected to be the inverse hyperbolic tangent function 3 $g(z)=tanh^{-1}(z)$.

The values generated for the present state x_n is thus a 4 function of the present input un and the values for the previous 5 state x_{n-1} . Since the previous state X_{n-1} depends on the previous 6 input u_{n-1} and the prior state x_{n-2} , the effect of the feedback is 7 recursive; that is, at any time t_n , the state x_n depends on the 8 sequence of past values $(x_{n-1}, x_{n-2} \dots)$ for the scenario under 9 Thus, the neural network 11(1) captures the 10 consideration. context of the present measurement by consideration of the past 11 history back to the beginning of the leg. 12

The output vector generated by the output nodes 23(0) is 13 generated in a similar fashion by $y_n = g(W_2x_n)$ where W_2 is the matrix 14 of neural network weights for the links 24(h)(o) interconnecting 15 the nodes 21(h) comprising the hidden layer and the nodes 23(o) 16 comprising the output layer. The output vector generated by the 17 nodes 23(o) comprising the output layer is given by $y_n = [B_m B_m]$ 18 R_n'/R_n , where B_m represents the bearing on leg (1), B_m represents 19 the bearing rate on leg (1), and R_n'/R_n represents the normalized 20 range rate on leg (1) at time t_n . 21

The neural network 11(1) continues to receive bearing measurements and ownship kinematic information for successive points in time until the observation ship changes to a second observation leg (2). At that point, the last state estimate generated by the neural network 11(1) is coupled as an initial

input state feedback to neural network 11(2) and subsequent. 1 2 bearing measurements and ownship kinematic information is coupled to that neural network 11(2). The neural network 11(2), which is 3 shown in FIG. 3, is constructed in a similar manner as neural 4 network 11(1), with the additional input to delay 37 providing 5 the initial input state feedback, x_{o2} . The particular initial 6 state provided by neural network 11(1) to 11(2), through delay 7 37, is provided by $X_{02} = W_2^+G^{-1}(Y_{N1})$, where W_2^+ is the pseudo-inverse 8 of the weight matrix W_2 and ${}^{\textbf{Y}_{N1}}$ is the final state estimate 9

10 generated by neural network 11(1) at the end of observation leg 11 (1).

12 The neural networks 11(1) and 11(2) can be trained using the 13 well-known conventional back-propagation method of training 14 neural networks, using data generated from simulated underwater 15 tracking scenarios in which trajectory information on the target 16 and ownship vehicles is recorded, and synthetic bearing 17 measurements are collected.

As indicated above, the data fusion system 12 may comprise a neural network or any other suitable mechanism for performing data fusion. The system 12 integrates the information from the neural networks 11(1) and 11(2) to provide a range estimate and update the bearing rate, normalized range-rate and bearing estimates using information from the various observation legs.

24The invention provides a number of advantages. In25particular, it provides an arrangement for readily processing

possibly noisy information in real time, thereby providing a timely response to dynamically evolving scenarios. Since the neural networks 11(1) and 11(2) have recurrent structures, through delays 27 and 37, they can process information through sliding time windows, while maintaining the history of the processing.

The preceding description has been limited to a specific 7 embodiment of this invention. It will be apparent, however, that 8 variations and modifications may be made to the invention, with 9 the attainment of some or all of the advantages of the invention. 10 11 For example, more than two neural networks can be utilized in the first level if more than two observation legs will be performed, 12 or alternatively a single neural network may be used which has 13 the characteristics of the combination of the two neural networks 14 11(1) and 11(2) described above. Therefore, it is the object 15 to cover all such variations and 16 17 modifications as come within the true spirit and scope of the 18 invention.

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3	SYSTEM FOR BEARINGS-ONLY CONTACT STATE
4	ESTIMATION USING RECURRENT NEURAL NETWORKS
5	
6	ABSTRACT OF THE DISCLOSURE
7	A system for bearings-only contact state estimation in
8	response to target bearing and ownship speed and course
9	information provided for a plurality of observation legs at
, 10	successive points in time, includes a plurality of neural
11	networks and a data fusion circuit. Each of the neural networks
12	generates range-normalized parameter estimate information for one
13	of the observation legs in response to target bearing and ownship
14	speed and course information for an associated one of the
15	observation legs, provided thereto at each point in time and
16	information generated for the previous point in time. The data
17	fusion system receives the range-normalized parameter estimate
18	information from the neural networks and generates the contact
19	state estimate in response thereto.

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F I G. 2



F I G. 3