A SHIP'S MINIMUM TIME MANEUVERING SYSTEM WITH NEURAL NETWORK AND NON-LINEAR MODEL BASED SUPER REAL-TIME SIMULATOR

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Abstract

In this paper a feasible ship's minimum-time maneuvering system is proposed. The proposed control system is mainly composed of a neural network based optimal solution generator and a non-linear model based super real-time simulator. In order to investigate the effectiveness of the proposed method, computer simulations and actual sea tests are carried out using a training ship *Shioji Maru*. The experimental results show that the proposed method is successfully applied.

1 Introduction

It is very important for a ship's master to draw up a ship-handling plan before approaching a berth, leaving it, altering the heading and so on. In order to cope with these problems, they are required to derive the maximum maneuverability from the ship. The minimum-time control technique is one of the rational and effective maneuvering methods for such tedious problems if the mathematical model representing a ship's dynamics is available. However, it should be noted that the model becomes highly non-linear, especially in the case of low speed and large maneuvering motion. In this case, the solutions of minimum-time maneuvering problem can be obtained by solving non-linear two-point boundary value problems (TPBVP).

In order to take enough account of the non-linearity, Shoji and Ohtsu [1] have formulated these problems as a non-linear, two-point boundary-value problem (TPBVP) in the calculus of variations. The problems have been solved, using the numerical method called the sequential conjugate gradient restoration (SCGR) method [2], [3] under various situations: 1) The minimum-time course-alteration problem, 2) The minimum-time stopping problem, 3) The minimum-time parallel deviation problem [4], 4) The minimum-time maneuvering problem with wind disturbances [5], 5) The minimum-time berthing problems [1], [6]. However, the solutions, unfortunately, do not yield on-line control laws, because, it took long computational time to obtain the optimal solution even by using a high-speed workstation. Moreover, the geometrical and other sea conditions of maneuvering problem facing to the real ship handling scenes are various. Thus, it is impossible to prepare whole minimum time maneuvering solutions to such various conditions.

For these problems, Okazaki et al., [7] have investigated the minimum time maneuvering with neural network. In the proposed method, an off-line trained neural network interpolates the real-time maneuvering solution from the available solutions, which has been already solved, but the control performance varies depend on the disturbances in real sea conditions. To overcome this problem, Mizuno et al., [8] have proposed a ship's minimum-time maneuvering system with two types of neural networks. This system contains the on-line trained neural network which compensates the difference between the real ship's dynamics and the mathematical model and the other errors caused by some disturbances etc. From the experimental results, the method has some advantages compared with the previous studies.

There are some papers in which the neural networks are used in order to compensate the non-linear dynamics of the ship during the tracking or berthing phase [9]-[13]. Unfortunately the on-line learning speed of the neural network is rather slow. This means that it is difficult to obtain the good transient performance for tracking or berthing in real situations.
From this point of view, we propose a new design method for ship's minimum time maneuvering system with neural network and non-linear model based super real-time simulator.

The proposed system is mainly composed of two parts. The one is a neural network based optimal solution generator and another is a non-linear model based super real-time simulator. The neural network generates the optimal solution for real situation by interpolating pre-computed minimum-time solutions for typical control conditions. The optimal solutions for the various minimum time maneuvering are numerically computed based on the sophisticated non-linear dynamical model of the ship and are learned off-line by the neural network for interpolation.

Moreover, the same non-linear dynamical model, which is used for the computation of the optimal solutions, is used to simulate the ship's future course in super real-time. Based on the computed ship's future course, the predicting control error caused by some disturbances is compensated by modifying the control input for minimum time maneuvering. This is an original feature of this system.

First, the solving technique of the minimum-time maneuvering problems and the mathematical model of the ship's dynamics are briefly reviewed. Next, the minimum-time parallel deviation maneuvering problem and its solutions are introduced as an example of the feasible study realized by proposed system. In the third part of this paper, a minimum-time maneuvering system with neural network and non-linear model based super real-time simulator is introduced. Finally, computer simulations and on-line experiments are carried out for a training ship *Shioji Maru* (425 gross tonnage).

2 Outline of solving technique of the minimum maneuvering problems

2.1 Formulation

The minimum time maneuvering problem is formulated to control a ship from a certain condition to another one in a minimum time. This kind of problem is considered as a two-point boundary value problem, in which an initial point as the one condition of the ship (for example, the starting point) and a terminal point as the another condition of the ship (for example, the stopping point).
Such control problem might be solved using the theory of calculus of variations. However, since ship's motion has high non-linearity, it is impossible to find an analytical solution. Thus it is inevitable to adopt some numerical methods for solving the problem. In this paper, the sequential conjugate gradient-restoration (SCGR) method developed by Miele et al. [1] was used.

The minimum time maneuvering problem is formulated as follows:
A performance index of this problem is defined by a functional

$$I = \int_0^1 f(x,u,t,t)dt = \int_0^1 t dt = t \tag{1}$$

where I is a scalar value, x is the state vector, u is the control vector, t is the actual final time value and t is the normalized time value.
And the solution of the problem is minimized the performance index with constrains as follows:
1) the differential constraints,

$$\dot{\mathbf{x}} - \Phi(\mathbf{x},\mathbf{u},t,t) = 0 \qquad 0 \le t \le 1 \tag{2}$$

where Φ denotes a non-linear hydro dynamic model for representing ship's motions, and
2) the boundary conditions:

i) The initial ship's state,

$$[w(x)]_0 = 0 \tag{3}$$

ii) The final state of the ship, specified by the function

$$[\Psi(\mathbf{x},t)]_1 = 0 \tag{4}$$

where the function Ψ is a q-dimensional vector ($0 \le q \le n$).
3) the non-differential constraints:

$$\mathbf{S}(\mathbf{x},\mathbf{u},t,t) = 0\,, 0 \le T \le 1 \tag{5}$$

may be added, by which it is possible to set the maximum limits of rudder angle, propeller blade angle, and power of the bow and stern thrusters, to be applied.

2.2 Ship's motion model

Shioji Maru is equipped with a bow and stern thrusters, besides a rudder and a controllable pitch propeller (CPP). Her principal dimensions are shown at Table 1 and the coordinate system is shown in Figure 1.

Table 1: Principal Dimensions of *Shioji Maru*

Length	49.93 m
Breadth	10.00 m
Tonnage	425.0 GT
Propeller	CPP
Bow Thruster	2.4 tons
Stern Thruster	1.8 tons

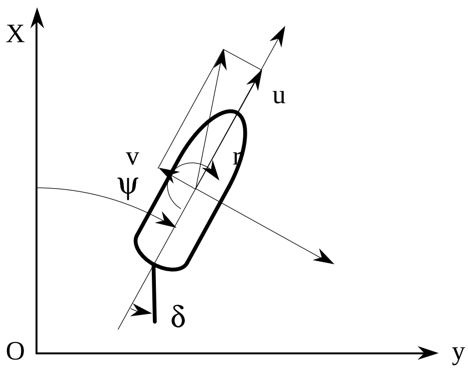

Fig. 1 Ship's coordinate in horizontal plane

The state values are ship's position (x, y), ship's heading y, surge speed u, sway speed v, yaw rate r, rudder angle d and CPP angle q_P The control values are order rudder angle d^*, order CPP angle q_P^*, notch of bow thruster bt^*, notch of stern thruster st^*. Referencing to this, the sophisticated mathematical model (called MMG model) is written by

$$\dot{x} = u\cos y - v\sin y \tag{6}$$

$$m(\dot{u} - vr) = X_H + X_P + X_R \tag{7}$$

$$\dot{y} = u\sin y + v\cos y \tag{8}$$

$$m(\dot{u} - vr) = X_H + X_P + X_R \quad (7)$$

$$\dot{y} = u \sin y + v \cos y \quad (8)$$

$$m(\dot{v} + ur) = Y_H + Y_T + Y_R + Y_{Th} \quad (9)$$

$$\dot{y} = r \quad (10)$$

$$I_{ZZ}\dot{r} = N_H + N_T + N_R + N_{Th} \quad (11)$$

$$\dot{d} = \frac{(d^* - d)}{(|d^* - d| T_{RUD} + a)} \quad (12)$$

$$\dot{q}_P = \frac{(q^*_P - q_P - \dot{q}_P T_{lp})}{T_{lp}(|q^*_P - q_P - \dot{q}_P T_{lp}| T_{CPP} + a)} - \frac{\dot{q}_P}{T_{lp}} \quad (13)$$

where m and I are the mass and the turning moment inertia. T_{RUD} , T_{CPP} and a are time constants. The subscripts H , P , R and T_h denote the highly non-linear hydrodynamic force induced by the hull, propeller, rudder and thruster. For detail of the hydrodynamic force, see [5].

2.3 Minimum-time parallel deviation maneuvering problem and the non-linearity of its solutions

In this paper, the minimum-time parallel deviation maneuvering problem and its solutions are considered as a simple example of the feasible study realised by proposed control system. Figure 2 shows the initial course line and terminal one of the minimum-time parallel deviation problem.

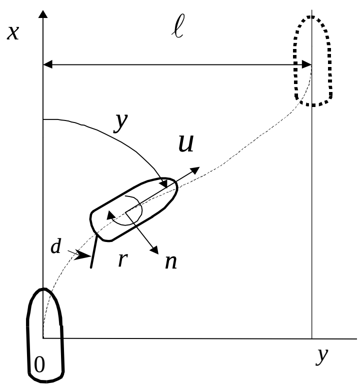

Fig. 2 Parallel deviation problem

Where ℓ is the distance between two parallel course lines. In this case, the boundary conditions for the two-point boundary value problem and the non-differential constraint are as follows.

1) The initial ship's state

$$[x(0) \quad y(0) \quad u(0) \quad v(0) \quad r(0) \quad y(0) \quad d(0)]^T = given \quad (14)$$

2) The final state of the ship

$$[y(1) \quad v(1) \quad r(1) \quad y(1) \quad d(1)]^T = [y_f \quad v_f \quad r_f \quad y_f \quad d_f]^T = 0 \quad (15)$$

3) the non-differential constraints

$$d^*(t) - \sin d_{Dumy}(t) = 0, \; 0 \le t \le 1 \quad (16)$$

where, d_{Dumy} is the dummy variable for the order rudder angle. Under these conditions, the minimum-time control solutions can be obtained using the SCGR method. The first examples are minimum-time deviation problems with different deviations. In this case, the ship must deviate 100m and 200m away from the initial approach line in a minimum maneuvering time, using the rudder. The ship's initial cruising speed is 12 knots, and the side ways speed must disappear and the head must be redirected on the original course after ending the deviation. Figure 3 shows the optimal paths and ship's headings in each case.

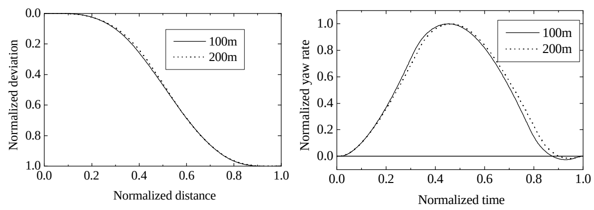

Fig. 3 The optimal path and heading for different course deviation

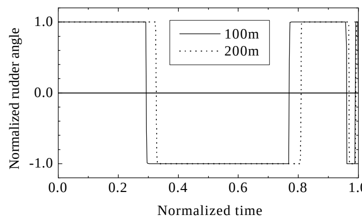

Fig. 4 The optimal time histories of rudder angles for different course deviation

Figure 4 shows the corresponding time histories of the rudder angles. It should be noted that the time histories of the heading angles have almost the same patterns, whereas those of the rudder angles are different in each case. This means that the ship's minimum-time maneuvering system should have the real-time ability to calculate the optimal solutions. However, even in the simple case mentioned above, it usually takes several minutes to compute the optimal solution for about one minute's maneuvering. Thus, more efficient algorithm is needed to implement the practical minimum-time maneuvering system.

3 Minimum-time maneuvering system with neural network and non-linear model based super real-time simulator

3.1 Optimal solution generator using neural network

In the proposed system, the real-time solution for a new maneuvering condition will be generated by interpolating the pre-computed solutions for typical conditions using neural network (NN).

Figure 5 shows the three layered neural network used in this research [7]. The inputs x_i for the neural network are the ship's state values, which include the ship's position from the terminal course line y, its heading y , and its speed V . The output of the neural network $o = \hat{d}$ corresponds to the rudder angle d_{OPT} for minimum-time

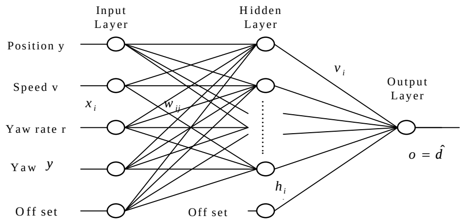

Fig. 5 Structure 3-layered neural network

maneuvering solution. In Fig.5 w_{ij}, v_i are synaptic weights between input and hidden layer, hidden and output layer respectively. The outputs of the hidden units are,

$$h_i = f(u_i) = f(\sum_i w_{ij} x_i + x_0) \tag{17}$$

And the output of the network are defined by

$$o = f(s) = f(\sum_i h_j v_j + h_0) \tag{18}$$

where, x_0, h_0 are the off sets for the inputs, and i , j denote the numbers of units in input and hidden layer respectively. The non-linear function $f(\cdot)$ in the unit is a sigmoid function of the form:

$$f(x) = 1/(1+e^{-x}) \tag{19}$$

As a learning algorithm for this network, the following back propagation method is adopted.

$$e = d_{OPT} - o \tag{20}$$

$$\Delta v_i(n) = h.e.f(s).(1-f(s)).h_i + a\Delta.v_l(n-1) \tag{21}$$

$$\Delta w_{ij} = h \cdot e.f(s).(1-f(s)).v_j).f(u_j).(1-f(u_j)).x_i + \Delta w_{ij}(n-1) \tag{22}$$

where Δ denotes the update quantity of each variables at iteration n . h and a are the learning rate and the momentum term. During the network training, the time series of ship state values are fed to the input layers and the network synaptic weights w_{ij}, v_{jk} are updated to reduce the error between the network output signal and the minimum-time maneuvering solutions d_{OPT} (optimal control values). After sufficient training, the neural network could make appropriate time series of control values (rudder angle d) for arbitrary minimum-time maneuvering within certain range of course deviation. Furthermore, the calculation time to interpolate these solutions is less than one second. In this case, the structure of the neural network (number of hidden units $j = 4$) is determined heuristically and verified by using AIC (Akaike's Information Criterion) and MDL (Minimum Description Length Principle) [14].

3.2 Compensation of tracking error by using MMG model based super real-time simulator

By using off-line trained neural networks proposed above, the optimal solutions for practical conditions can be computed as "closed loop configuration" in real-time and a ship's minimum-time maneuvering may be implemented by the basic structure as shown in Fig.6.

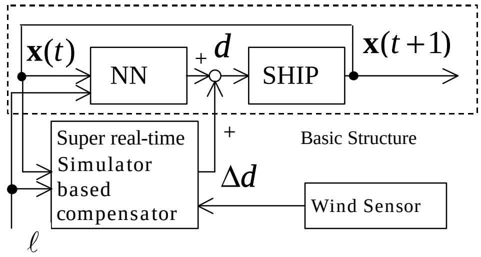

Fig. 6 Proposed minimum-time maneuvering system with super real-time simulator based compensator

However, from practical point of view, some disturbances (for example, wind and tidal current etc.) should be taken into account. We can combine the on-line trained neural network which compensates the error between the optimal route in minimum-time maneuvering and the real route of the controlled ship [8]. However, it is hard to find the design parameters which assures the good trasient performace. For this problem, we recommend to introduce the super real-time simulator based compensator into the control system instead of the on-line learning neural network as shown in Fig. 6, because we have already construct the sophisticated non-linear dynamical model (MMG model) of the ship and can use it.

In the proposed system, "Super real-time simulator based compensator" contaions the MMG model based ship's dynamic simulator and the search mechanizum for optimal rudder compensation Δd to reduce the tracking error based on the cost function J as described later. Note that the term "Super real-time" means that the MMG model based ship's accurate dynamic simulation can be carried out faster than the real ship's dynamic behaviour. Although the MMG model is very complicated, the computational time is very short compared with the time which is required for solving the optimal solution by SCGR method with MMG model. For example, the computational time for simulating the future 150 [sec] ship's behaviour is only 1.2 [msec] using the computer with the Celeron CPU at 500MHz clock. This means that we can simulate about 500 times with different conditions during the sampling period 1 [sec] in experiment.
To simulate the future behaviour of the ship, not only the accurate dynamical model but also the future input for the ship. For this problem, we can use the neural network based optimal solution generator "NN" for generate the future control values to the ship as shown in Fig. 7, because the generation of the solution (rudder order) is performed in closed loop configuration mentioned before.

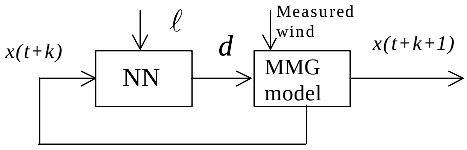

Fig. 7 Structure of super real-time simulator

By using the super real-time simulator, we optimise the following cost function J to reduce the tracking error for the optimal course of the minimum time maneuvering.

$$\left.\begin{aligned} J &= \sum_{k=L}^{P} |\ell - Y(k)| \qquad (0 \le t < L) \\ J &= \sum_{k=t+1}^{P} |\ell - Y(k)| \qquad (L \le t \le P) \end{aligned}\right\} \tag{23}$$

First, the super real-time simulation is carried out assuming the rudder compensation Δd as an appropriate setting for the future time period [t,P] and the value of J is calculated as the "error area" for [L,P] as shown in Fig. 8. Next, to optimise the cost function, the simulation and evaluation are repeated based on the linear search as shown in Fig. 9.

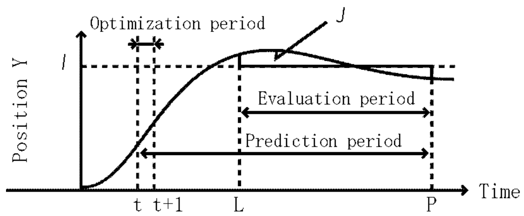

Fig. 8 Simulation and evaluation period for optimization

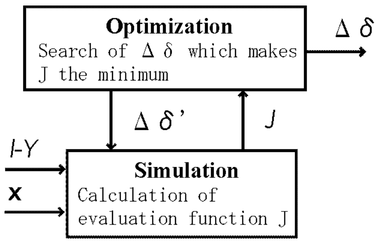

Fig. 9 Optimization mechanism by super real-time simulator

The above algorithm leads to the implementation of a kind of non-linear model based predictive controller. In this case, the stability of the overall system is very important. However, it is very difficult to prove the stability of the non-linear control system theoretically. In this system, we can assure the practical stability of the controller by supervising and restricting the output of the super real-time simulator based compensator.

4 Preliminary evaluation by computer simulations

Before implementing the proposed minimum-time maneuvering system, computer simulations of both basic and proposed scheme are performed for non-linear dynamical model of the *Shioji Maru*. Figure 10 and 11 show the simulation results for minimum-time deviation problem with wind disturbances by using basic (NN only) and proposed (NN+Super real-time simulator) control system respectively. The ship must deviate 150 m away from the initial course line. In these cases, the winds blow from the port (90[deg]) at relative wind velocities of 10 m/sec. The neural network "NN" in both the basic and proposed maneuvering system has been off-line trained using the four minimum time solutions with $\ell = 100m$ and $200m$ for the ship speed $u = 5.0m/s$ *and* $6.6m/s$ under the constraint of $|d| \le 5$[deg]. For the proposed method, the optimal value of the rudder compensation Δd is searched in the range of ± 4.0[deg] with the resolution of 0.4[deg]. Moreover, for the safe of ship's maneuvering, the maximum rudder order is restricted as $|d + \Delta d| \le 7.0$[deg]. Moreover, the same MMG model is used to simulate the ship's bahaviour and is used in super real-time simulator. In these figures, the dashed lines show the minimum time solution for wind free case and the solid lines are with wind disturbance. From these results, it should be noted that the error between the ship's dynamics and the actual one does not exist, whereas the path obtained using only NN is rather different from the optimal one. Thus, it is generally concluded that the control system should have a feedback compensator, in order to avoid the influence of disturbances. The next two simulation results show the control performances with modeling error (the case real weight of the ship is 80 % of the assumed weight in the model) for basic system (Fig. 12) and for proposed system (Fig. 13). From these results, it can be seen that the proposed system has a superior performance compared with the basic one.

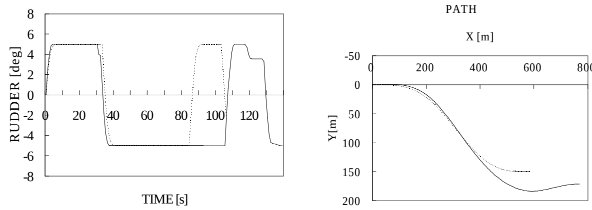

Fig. 10 Simulation results of basic minimum-time maneuvering system with wind

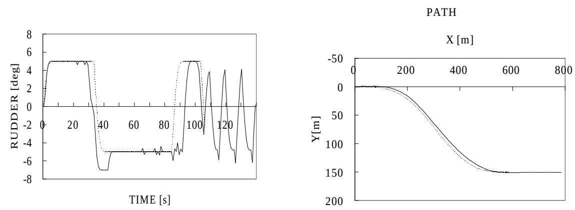

Fig. 11 Simulation results of proposed minimum-time maneuvering system with wind

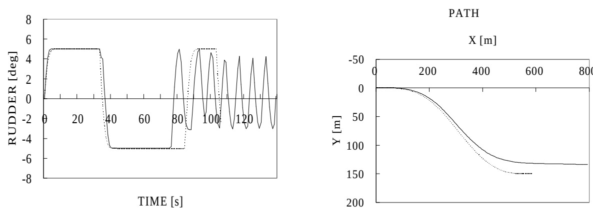

Fig. 12 Simulation results of basic minimum-time maneuvering system with weight error

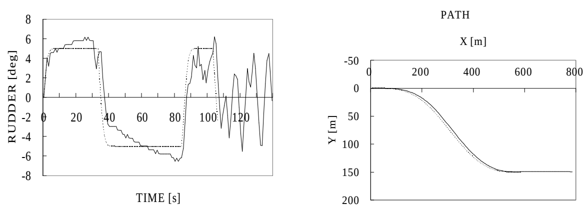

Fig. 13 Simulation results of proposed minimum-time maneuvering system with weight error

5 Actual sea test

5.1 The training ship Shioji Maru

Fig. 14 A picture of *Shioji Maru*

In order to evaluate the feasibility of the proposed minimum-time maneuvering system, the actual deviation tests were carried out at sea, using the *Shioji Maru* of Tokyo University of Mercantile Marine.(Fig. 14).

5.2 Real Time Control System

Figure 15 shows one of the real time control systems aboard the *Shioji Maru*. On board the training ship, GPS signals are available to provide accurate positions of ships. The GPS signals are obtained from the GPS receiver and distributed to the computers for real time control.

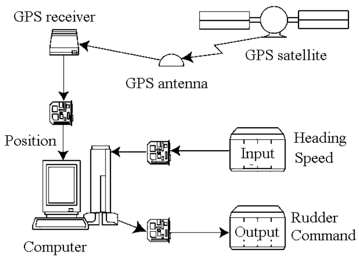

Fig. 15 Real time control systems on board

5.3 Experimental results

In the sea trials, the distance between the initial course line and the final one was set up as distance of 150 m. The control laws implemented in the computer were the basic scheme with NN, the proposed one with NN+Super real-time simulator. Figure 16 shows the typical experimental result. The right traces show ship's actual path measured through a GPS (solid line), and the optimal one (dashed line) and the left the calculated rudder angle and optimal one under actual conditions with about 12m/s wind from the bow side. In these cases, the settings for the controller are same as the simulation. From this result, it can be concluded that the proposed minimum-time maneuvering system with NN+Super real-time simulator is feasible in actual sea conditions.

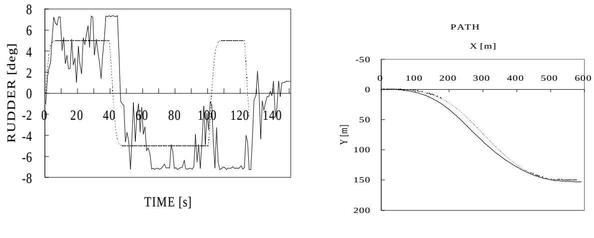

Fig. 16 The typical path and the time histories of rudder angles at actual automatic deviation tests

6. Conclusion

This paper presented a practical ship's minimum-time maneuvering system with neural network and non-linear model based super real-time simulator. In the minimum-time deviation problems, the system gives approximate solutions in a short computing time and good tracking performance in real situations. Moreover, the actual sea trials demonstrate the effectiveness of the proposed system.

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