Parameters identification for ship motion model based on particle swarm optimization

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Abstract

Purpose – The purpose of this paper is to identify the Nomoto ship model parameters accurately, in order to produce a very close match between the predictions based on the model and the full-scale trials.

Design/methodology/approach – Various ship maneuvering mathematical models have been used when describing the ship dynamics behavior. The Nomoto ship model is a class of simplified hydrodynamic derivative type models which are the most widely used, accepted and perhaps well developed. To determine the model parameters accurately, particle swarm optimization (PSO) is chosen as an evolution algorithm in this paper. This arithmetic can guarantee the convergence and global optimization ability, and avoid sinking into a local optimal solution.

Findings – The process of PSO for identifying the Nomoto ship model parameters is given.

Research limitations/implications – Availability of the full-scale trial data are the main limitations.

Practical implications – The ship model parameters provide very useful advice in ship's autopilot process.

Originality/value – The paper presents a new parameter identification method for the second-order Nomoto ship model based on PSO.

Keywords Cybernetics, Motion, Modelling, Ships, Programming and algorithm theory

Paper type Technical paper

1. Introduction

Various approaches have been adopted when describing the ship dynamics behavior, such as system identification approach, slender-body approximation approach, hydrodynamic derivative type modelling approach, etc. (Pourzanjani and Vahedipour, 1991; Pourzanjani, 1990; Pourzanjani *et al.*, 1987; Crane *et al.*, 1989). System identification is a control engineering approach and is based on defining the systems equations from a set of experimental results. For a more general study on systems, pleaser refer to Lin (1987) and Lin and Ma (1993). Slender-body approximation is employed to estimate the

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forces acting on the marine hull forms, as discussed by Pourzanjani and Vahedipour (1991) and Pourzanjani *et al.* (1987). The reason for this special treatment of hull hydrodynamic forces is that these are relatively large and also contain the main inherent nonlinearities of the ship. The most widely used, accepted and perhaps well developed model, is the traditional hydrodynamic derivative type modelling approach where the sum of forces and moments acting on the body are expanded using Taylor series expansion of a function of various variables (Crane *et al.*, 1989) (for a critical discussion on this approach, see Lin (1998) and OuYang *et al.* (2000)). These models have since been developed much further and are being used in areas such as port design, ship design, autopilot design, training, and research (Pourzanjani, 1990). When developing a model for these purposes, points which should be taken into account are that the model should be a true and accurate representative of the real system, and evaluation of the parameters for the model should be easy and practicable.

The Nomoto ship model (Pourzanjani and Vahedipour, 1991; Xinyue and Yansheng, 1999; Meng *et al.*, 2006) is a class of simplified hydrodynamic derivative type models. In order to produce very close match between the predictions based on the second-order Nomoto ship model and the full-scale trials, it is important to determine the model parameters accurately. Some algorithms have been developed to do that, such as the least-squares algorithm, maximal likelihood function algorithm (Ljung, 1978) and genetic algorithm (Meng *et al.*, 2006), etc. In this paper, a new algorithm based on particle swarm optimization (PSO) is proposed for identifying the model parameters. The arithmetic can guarantee the convergence and globally optimal ability, and avoid sinking into a local optimal solution. The last simulation results demonstrate the feasibility and effectiveness of the proposed identification algorithm.

The rest of this paper is organized as follows. In Section 2, ship motion models are introduced. In Section 3, the proposed parameter identification algorithm for the Nomoto ship models is explained in detail based on PSO. To illustrate the usefulness of the proposed identification algorithm, Section 4 presents some simulation examples. A short conclusion is made in the final section.

2. Model of ship motion

In the 1970s of the last century, the Ship Manoeuvring Mathematical Model Group from Japan proposed the MMG model. Its main feature is dividing the hydrodynamic forces and moments acting on ships into that on the nude body, hull and rudder of the ships, and that interacting on each other. The MMG model chooses the ship center of gravity as the origin of the body fixed coordinate system. According to the Newton's second law of motion, a three degrees of freedom MMG model can be written as:

$$\begin{aligned} m(\dot{u} - v\dot{\psi}) &= X \\ m(\dot{v} + u\dot{\psi}) &= Y \\ I_{zz}\ddot{\psi} &= N - Y \cdot x_C \end{aligned} \tag{1}$$

where, u, v, ψ are the surge velocity, sway velocity, and course of the ship, respectively, x_C is the x-coordinate of the center of ship.

The right-hand side of equation (1) can conveniently be written in terms of various contributors (such as hull, rudder, etc.) to these forces, then equation (1) can be expressed as follows:

$$
\begin{aligned}
m(\dot{u} - v\dot{\psi}) &= X_I + X_H + X_P + X_R \\
m(\dot{v} + u\dot{\psi}) &= Y_I + Y_H + Y_P + Y_R \\
I_{zz}\ddot{\psi} &= N_I + N_H + N_P + N_R - Y \cdot x_C
\end{aligned} \tag{2}
$$

The sum of forces and moments acting on the body (the right-hand side of equation (2)) can be expanded using Taylor series expansion of a function of various variables. Noting the symmetry of the hull and some other considerations, some of the terms can be omitted. Further higher order terms which are assumed to have little influence on the forces are neglected. Assume that the forward velocity remains constant during small heading changes, with the inclusion of the rudder forces and assumption of small variations in yaw and sway, the governing equations of motion can be linearized to form a single equation relating the rudder movement to yaw as follows:

$$T_1T_2\dddot{\psi} + (T_1 + T_2)\ddot{\psi} + \dot{\psi} = K(\delta + T_3\dot{\delta}) \tag{3}$$

where, ψ is the course of the ship, δ is the rudder angle. Model (3) was first developed by Nomoto, and different versions of this (some of which include some nonlinearities) have been used very extensively to design and develop controllers for ships. When ship moves under low-frequency circumstances, $T = T_1 + T_2 + T_3$, and equation (3) can be simplified as:

$$T\ddot{\psi} + \dot{\psi} = K\delta \tag{4}$$

In any real systems, noise interference is unavoidable, considering the random noises when ship sails at the sea, model (4) can be written as:

$$T\ddot{\psi} + \dot{\psi} = K(\delta + w) \tag{5}$$

where, w is the sum of various random noises, which can be regarded as the random interference to the rudder angle.

For model (4), denote r to be the yaw rate of the ship, then $\dot{\psi} = r$, and model (4) can be expressed as:

$$T\dot{r} + r = K\delta \tag{6}$$

Correspondingly, model (5) can be expressed as:

$$T\dot{r} + r = K(\delta + w) \tag{7}$$

In the next section, a new algorithm based on PSO is proposed for identifying the model parameters K and T.

3. PSO for identifying the model parameters

3.1 Principle of PSO

Kennedy and Eberhart (1995) proposed PSO algorithm in 1995. Social behavior of organisms such as bird flocking and fish schooling motivated them to look into the effect of collaboration of species onto achieving their goals as a group. Years of study for the dynamics of bird flocking resulted in the optimization tool, PSO. In a PSO system, multiple candidate solutions coexist and collaborate simultaneously. Each solution candidate, called a "particle," flies around in a multidimensional search space looking for the optimal solution. Particles then may adjust their positions according to the experience of their own and their neighboring particles, moving towards their best positions or the best positions of their neighbors. In order to achieve this, a particle keeps previously reached "best" positions in memory. PSO system combines local search methods (through self experience) with global search methods (through the experiences of their neighbors), attempting to balance exploration and exploitation. Two factors characterize a particle status on the search space: its position and velocity (Salman *et al.*, 2002). Let $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ be the position of particle i, $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ be its velocity, where v_{id}, $1 \leq d \leq D$, represents the distance to be traveled by the particle from its current position, x_{id}, in unit time, $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ be its best previous position; $P_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$ be the best position among all particles in the population. The following equations are used to manipulate the position and velocity:

$$v_{id}(t+1) = wv_{id}(t) + c_1 \cdot Rand1() \cdot [p_{id}(t) - x_{id}(t)] + c_2 \cdot Rand2() \cdot [p_{gd}(t) - x_{id}(t)] \quad (8)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (9)$$

where, *Rand1* and *Rand2* are two random functions with a range [0,1]; acceleration coefficients, c_1 and c_2, are positive constant parameters, which control the maximum step size of the particle; the inertia weight, w, is a user-specified parameter that controls, together with c_1 and c_2, the impact of previous historical values of particle velocities on its current one, making a balance between global exploration and local search. In general, a bigger w can guarantee the globally search ability, and avoid sinking into a local optimal solution. On the contrary, a smaller w is good for local search, and can guarantee the convergence of the arithmetic. Shi and Eberhart (1998) proposed a self-adaptive adjusted strategy for inertia weight w as follows:

$$w(t) = w_{\max} - \frac{t}{T}(w_{\max} - w_{\min}) \quad (10)$$

where, t is the current iteration generation, T is the maximum iteration generation, $w_{\max}$ and $w_{\min}$ are the maximum and minimum inertia weight, respectively.

Equation (8) is used to update the particle's velocity according to its previous velocity and the distance from its current position to both the best historical position of its own and that of all its neighbors. Then the particle flies toward a new position according to equation (9). The performance of each particle is measured according to a predefined fitness, which is usually proportional to the cost function associated with the problem. This process is repeated until user-defined stopping criteria are satisfied or the maximum iteration generation is reached.

3.2 Representation and fitness evaluation of particle

One of the key issues in developing a successful PSO algorithm is to find a suitable mapping between problem solution and PSO particle.

3.2.1 Representation and fitness evaluation of PSO particle for model (6). For model (6) which does not consider the random noises, denote $\dot{r}(n) = (r(n) - r(n-1))/T_s$, we can obtain the discrete model as follows:

$$r(n) = a \cdot r(n-1) + b \cdot \delta(n) \quad (11)$$

where, $a = 1/(1 + (T_s/T))$, $b = ((K \cdot T_s)/(T + T_s))$.

To identify the parameters K and T for model (6), we can choose two-dimension vector $X = (a, b)$ to be PSO particle. Suppose the estimate value of vector X to be $\hat{X} = (\hat{a}, \hat{b})$, then, the error of estimation can be evaluated by following function:

$$J = \sum_{n=1}^{N} [r(n) - \hat{r}(n)]^2 = \sum_{n=1}^{N} [r(n) - \hat{a} \cdot r(n-1) - \hat{b} \cdot \delta(n)]^2 \tag{12}$$

So, the fitness function for particle $X = (a,b)$ is defined as follows:

$$Fitness(X) = \frac{1}{1 + \sum_{n=1}^{N} [r(n) - \hat{a} \cdot r(n-1) - \hat{b} \cdot \delta(n)]^2}. \tag{13}$$

3.2.2 Representation and fitness evaluation of PSO particle for model (7). For model (7) which considers the colored noises, we can obtain the discrete form of Z transformation as follows (Meng *et al.*, 2006):

$$(1 - az^{-1}) \cdot r(n) = b \cdot \delta(n) + b \cdot w(n) \tag{14}$$

where, $w(n)$ is colored noise. It can be obtained by a white noise $\varepsilon(n)$ using Markov process transform, that is:

$$w = \frac{K_1}{T_1 s + 1} \cdot \varepsilon \tag{15}$$

Discreting (15), we have:

$$w(n) = \frac{d}{1 - cz^{-1}} \cdot \varepsilon(n) \tag{16}$$

where, $c = 1/(1 + (T_s/T_1)), d = ((K_1 \cdot T_s)/(T_1 + T_s))$.

So, equation (14) can be expressed as follows:

$$(1 - az^{-1}) \cdot (1 - cz^{-1}) \cdot r(n) = b \cdot (1 - cz^{-1}) \cdot \delta(n) + bd \cdot \varepsilon(n) \tag{17}$$

From equation (17), we can obtain:

$$r(n) = (a + c) \cdot r(n-1) - ac \cdot r(n-2) + b \cdot \delta(n) - bc \cdot \delta(n-1) + bd \cdot \varepsilon(n) \tag{18}$$

Let $\varepsilon'(n) = bd \cdot \varepsilon(n)$, $\varepsilon'(n)$ is also a white noise, $E(\varepsilon'(n)) = 0$. Equation (18) can be written as:

$$r(n) = (a + c) \cdot r(n-1) - ac \cdot r(n-2) + b \cdot \delta(n) - bc \cdot \delta(n-1) + \varepsilon'(n) \tag{19}$$

In the PSO system, we can choose three-dimension vector $X = (a, b, c)$ to be PSO particle. Suppose the estimate value of vector X be $\hat{X} = (\hat{a}, \hat{b}, \hat{c})$, then, the error of estimation can be evaluated by following function:

$$\begin{aligned} J &= \sum_{n=2}^{N} [r(n) - \hat{r}(n)]^2 \\ &= \sum_{n=2}^{N} [r(n) - (\hat{a} + \hat{c}) \cdot r(n-1) + \hat{a}\hat{c} \cdot r(n-2) - \hat{b} \cdot \delta(n) + \hat{b}\hat{c} \cdot \delta(n-1)]^2 \end{aligned} \tag{20}$$

So, the fitness function for particle $X = (a, b, c)$ can be defined as follows:

$$Fitness(X) = \frac{1}{1 + \sum_{n=2}^{N}[r(n) - (\hat{a}+\hat{c})\cdot r(n-1) + \hat{a}\hat{c}\cdot r(n-2) - \hat{b}\cdot \delta(n) + \hat{b}\hat{c}\cdot \delta(n-1)]^2}. \tag{21}$$

3.3 Process of PSO

Assuming that N is the set of the PSO population, $PSO[i]$ the ith particle of the PSO population, and G_{best} the index of the global best position found by all particles of the whole population. $PSO[i].fitness$, $PSO[i].Velocity$, and $PSO[i].Position$ are defined as the fitness, velocity, and position of the ith particle, respectively, where the later two are n-dimension vectors. Let $PSO[i].P_{best}$, be the position of the local best position for the ith particle. Then the process of PSO can be described as follows:

Step 1: initialisation. For each particle i of the population:

Step 1.1. Initialize $PSO[i]$ randomly, including velocity and position.

Step 1.2. The elements of the position vector of the ith particle are mapped into a valid candidate solution.

Step 1.3. Evaluate fitness $PSO[i].fitness$.

Step 1.4. Initialize $PSO[i].P_{best}$ with a copy of $PSO[i].Position$.

Step 1.5. Initialize G_{best} with the index of the best fitness particle.

Step 2: evolution. Repeat until a stopping criterion is satisfied:

Step 2.1. For each particle i, update $PSO[i].P_{best} = PSO[i].Position$ if and only if $PSO[i].fitness > PSO[i].P_{best}.fitness$.

Step 2.2. For each particle i, update $PSO[i].Velocity$ and $PSO[i].Position$ according to equations (8) and (9).

Step 2.3. For each particle i, the position vector of the particle is mapped into a valid candidate solution and its fitness $PSO[i].fitness$ is evaluated.

Step 2.4. Find G_{best} satisfying $PSO(G_{best}).fitness \geq PSO[i].fitness$, $\forall\, i \in N$.

4. Simulation results

The proposed PSO algorithm for identifying the model parameters is implemented in MATLAB programming language on an Intel 2.66 GHz, 512-MB personal computer running under Windows environment.

For model (6), to measure the effectiveness and viability of PSO algorithm, we specify $K = 0.05\,\mathrm{s}^{-1}$, $T = 30\,\mathrm{s}$, let $T_s = 0.5\,\mathrm{s}$, $r(0) = 0$, according to equation (11), 100 sample datum are generated. The parameters of PSO are set up as follows: $C_1 = 2$, $C_2 = 1.8$; $w_{\max} = 0.9$, $w_{\min} = 0.4$, population size is 20; maximum evolutionary generation is 100. Actually, according to the sample datum, PSO finds the actual values of K and T after 30 generations. The evolution process of K and T are shown in Figures 1 and 2.

For model (7) with colored noises, we first specify $K = 0.05\,\mathrm{s}^{-1}$, $T = 30\,\mathrm{s}$, $T_1 = 0.5\,\mathrm{s}$. Since $\varepsilon'(n)$ in equation (19) is a white noise, it can be supposed to be a random variable, having normal distribution, $\varepsilon'(n) \sim N(0, 0.0001^2)$. Let $T_s = 0.5\,\mathrm{s}$, $r(0) = 0$, $r(1) \approx 0$, according to equation (19), 100 sample datum are generated. The parameters of PSO are set up as follows: $C_1 = 2$, $C_2 = 1.8$; $w_{\max} = 0.9$, $w_{\min} = 0.1$, population size is 30; maximum evolutionary generation is 100. Implementing PSO

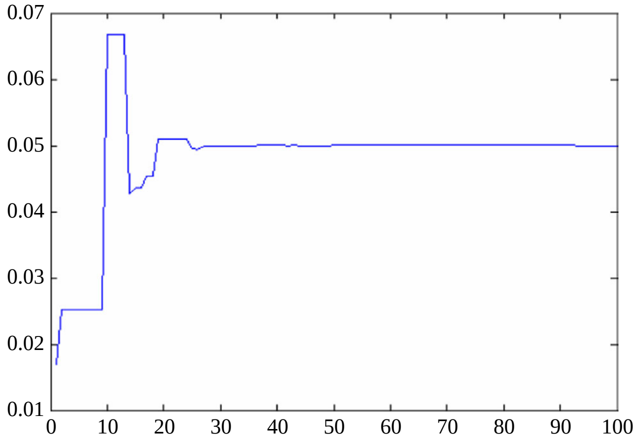

Figure 1.
The evolution process of K

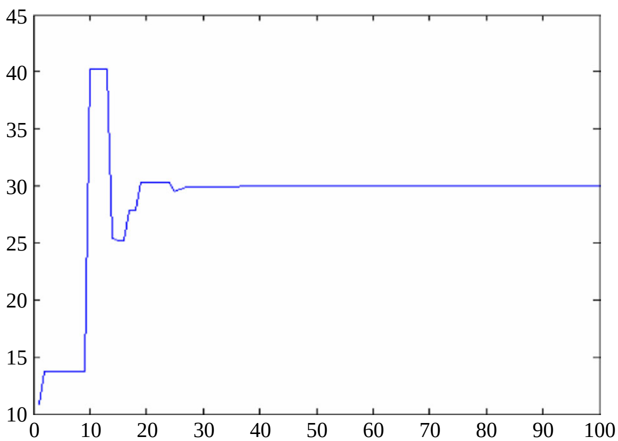

Figure 2.
The evolution process of T

algorithm ten times, the ten identification results are shown in Table I. Figures 3-5 show the evolution processes of the first identification results of K, T, and T_1, respectively. To measure the effectiveness and viability of PSO algorithm for model (7) with different colored noises, we furthermore specify $T_1 = 5\,\mathrm{s}$ and other parameters are the same as above. The corresponding identification results are given in Table II.

From Table I, we can obtain the average identification values of K, T, and T_1 are 0.04998, 29.98717, and 0.50035, the identification errors are 0.04, 0.0428, and 0.07 percent, respectively. From Table II, we can obtain the average identification values of K, T, and T_1 are 0.05012, 30.26307, and 4.96909, the identification errors are 0.24, 0.8769, and 0.6182 percent, respectively. The simulation results show that the proposed PSO algorithm is effective and valid for identifying the Nomoto ship model parameters.

5. Conclusions

Hydrodynamic derivative type modelling approach is the most widely used, accepted and perhaps well-developed ship motion model. In this paper, we consider the

Table I.
The identification results for $K = 0.05$, $T = 30$, $T_1 = 0.5$

	K	T	T_1
1	0.0499	29.9110	0.5059
2	0.0497	29.8846	0.5079
3	0.0500	29.9562	0.4994
4	0.0502	30.0441	0.4994
5	0.0499	29.9084	0.5049
6	0.0502	30.0533	0.4966
7	0.0499	30.0929	0.4950
8	0.0500	29.9521	0.4988
9	0.0500	30.0242	0.5008
10	0.0500	30.0449	0.4948

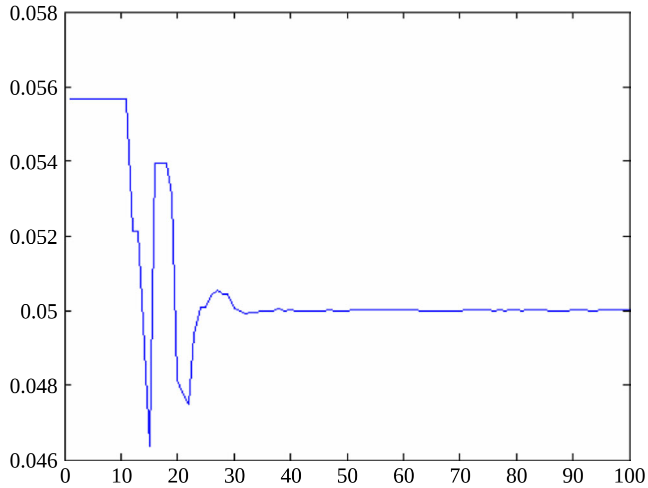

Figure 3.
The evolution process of K

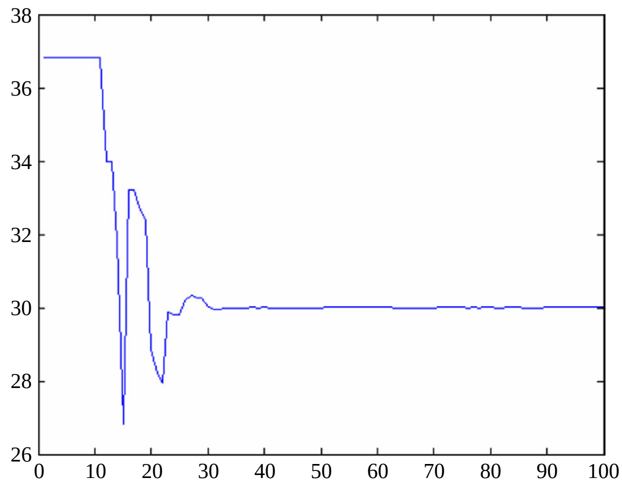

Figure 4.
The evolution process of T

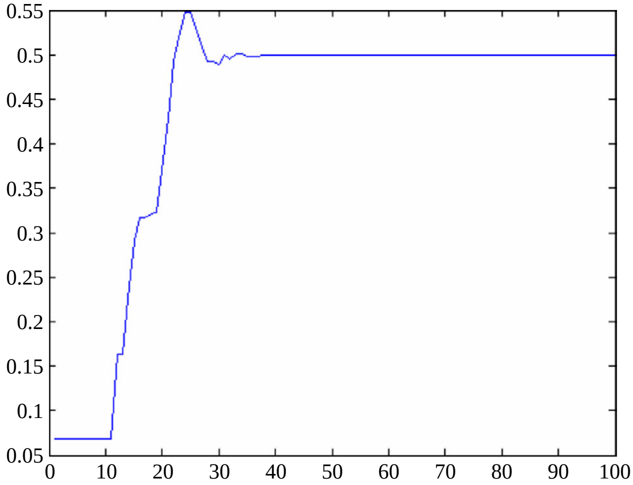

Figure 5. The evolution process of T_1

	K	T	T_1
1	0.0500	30.1850	4.9924
2	0.0500	30.4606	4.9420
3	0.0499	29.9850	4.9614
4	0.0500	30.3423	4.9266
5	0.0511	30.4020	5.0393
6	0.0494	29.5681	4.9442
7	0.0497	30.2086	4.9095
8	0.0497	30.3049	5.0722
9	0.0506	30.5811	4.9557
10	0.0508	30.5931	4.9476

Table II. The identification results for $K = 0.05$, $T = 30$, $T_1 = 5$

second-order Nomoto ship models which are a class of simplified hydrodynamic derivative type models. In order to produce very close match between the predictions based on the Nomoto ship models and the full-scale trials, a new algorithm based on PSO is proposed for identifying the model parameters. Simulation results show that the proposed arithmetic is effective and valid, it can guarantee the convergence and globally optimal ability, and avoid sinking into a local optimal solution. Since the second-order Nomoto ship models we considered in this paper are relatively simple, the parameter identification for more complex ship models using evolution algorithm will be our future work.

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