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Particle Swarm Optimization based modelling of a surface ship using free running experimental approach

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Abstract. System modelling of the surface ship, which could be regarded as a multi-variable parameter estimation problem, has attracted tremendous interests from researchers since it is of key importance to development of ships' control system. The aim of this study is to utilize the Particle Swarm Optimization (PSO) algorithm to get the optimized solution of hydrodynamic coefficients in the presence of ship's mathematical model using the space search principle. The motion equations of the ship in four degrees of freedom are formulated to clarify the scheme of the model. After expressing the theory of the PSO method, the system identification of the ship's motions is conducted to estimate the hydrodynamic coefficients. By using the identified parameters, the mathematical motion model of the free-running ship, namely 'P and O Nedlloyd Hoorn', is developed. The comparison between the experiment measurements and simulation trails and attitudes have indicated that the developed mathematical is sufficient and effective to response the ship's motions. Therefore, it is demonstrated that the PSO based system identification algorithm is capable of conducting system identification and system modelling for the surface ship through free running approach.

1. Introduction

Developing ship's mathematical model for promoting the autonomous requires parameters with satisfactory accuracy to formulate motion equations, which represent equivalent motion response as the real ship. Yet, it is a challenge to develop a promising mathematical model, since tremendous parameters are needed to show the ship's motions with high degree of complexity. These parameters constitute the rigid-body items, hydrodynamic added mass, as well as the hydrodynamic coefficients, which are determined by the means of system identification approaches to avoid over-parametrization [1].

In decades, some of the studies have worked the system identification method for the estimation of the hydrodynamic coefficients [2]. In recent years, the Least Square Variant method was applied to conduct the system identification and developed the ship's model with some success in [3]. However, these algorithms rely on the accuracy of the acquired data. When there exists obvious observation noises and deviation, it will cause the optimum to the disparate identification results.

At present, the Particle swarm optimization (PSO) has attracted some attention in conducting the modelling because of its pros of simple concept and easy conduction in optimization [4]. The PSO algorithm is a stochastic population-based computer algorithm modelled on swarm intelligence, which is developed from the social-psychological principles and provides insights into social behaviors, as well as contributing to engineering applications. Considering its capability in low computational expensiveness and quick convergence, the PSO based parameter estimation method was adopted to address the problem of system identification and modelling in this study.

The study is organized as follows. The mathematical model of the ship's motion in four Degrees of Freedom (DOF) is formulated in section 2. The PSO based parameter estimation method is presented in the following section. Section 4 details the experiments of the free-running ship conducted to identify the hydrodynamic coefficients, which were validated by comparing the experimental observation data and simulation trails from the developed mathematical model. In section 5, the conclusion is drawn.

2. Mathematical equation of modelling problem

For representing the ship's motions, the Newton-Euler's law is employed to derive ship's mathematical model, in which the items are generally clarified in the earth-fixed frame and body-fixed frame as shown in figure 1.

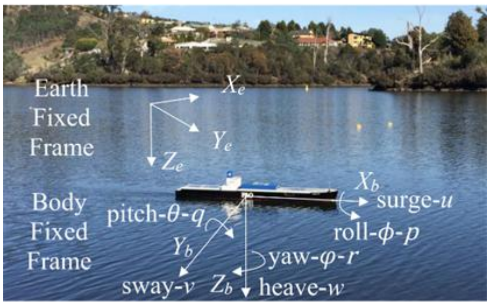

Figure 1. Frames of the ship's motions.

The four DOF nonlinear model including control forces and maneuvering characteristics in the degrees of surge, sway, yaw and roll can be expressed as [5]:

$$
\begin{cases}
(m+m_x)\dot{u} - (m+m_y)vr - F_R^X - T = X_{uu}u^2 + X_{vr}vr + X_{vv}v^2 + X_{rr}r^2 + X_{\phi\phi}\phi^2 \\
(m+m_y)\dot{v} + (m+m_x)ur + m_y\alpha_y\dot{r} - m_y l_y\dot{p} - F_R^Y = Y_v v + Y_r r + Y_{vvv}v^3 + Y_{vvr}v^2 r \\
\qquad + Y_{vrr}vr^2 + Y_{vv\phi}r^2\phi \\
(I_x+J_x)\dot{p} + m_y l_y\dot{v} - m_x l_x uv + W\overline{GM}\phi - F_R^K = K_v v + K_r r + K_p p + K_{vvv}v^3 + K_{vvr}v^2 r \\
\qquad + K_{vrr}vr^2 + K_{vv\phi}v^2\phi + K_{rr\phi}r^2\phi \\
(I_z+J_z)\dot{r} + m_y\alpha_y\dot{v} - F_R^N = N_v v + N_r r + N_p p + N_{vvv}v^3 + N_{rrr}r^3 + N_{vvr}v^2 r + N_{vrr}vr^2 \\
\qquad + N_{vv\phi}v^2\phi + N_{v\phi\phi}v\phi^2 + N_{rr\phi}r^2\phi + N_{r\phi\phi}r\phi^2
\end{cases}
\tag{1}
$$

where m is the ship's mass, m_x and m_y are the added masses with respect to the corresponding directions, I_x and I_z are the moments of inertia, J_x and J_z are the added inertial moments, u and v are the velocities of surge and sway, p and r are roll rate and yaw rate, W is the weight of the ship, $\overline{GM}$ is the metacentric height, ϕ is the a roll angle, α_y is the centre of m_y, l_x and l_y are the z-coordinates of the centres of m_x and m_y; T is the thrust force from propeller; F_R^X, F_R^Y, F_R^K and F_R^N are the forces and moments of the rudder in terms of the surge, sway, roll and yaw respectively; where $X_\bullet$, $Y_\bullet$, $K_\bullet$ and $N_\bullet$ with subscripts are the hydrodynamic coefficients in the corresponding degrees of freedom.

The terms on the left side of equation (1) can be computed based on the characteristics of the ship and hydrodynamic software program. In view of conducting system identification, the terms on the right side can be rewritten as:

$$\mathbf{H} = \Phi\mathbf{P} \tag{2}$$

where $\mathbf{H} = [\mathbf{X}_\mathrm{H} \quad \mathbf{Y}_\mathrm{H} \quad \mathbf{K}_\mathrm{H} \quad \mathbf{N}_\mathrm{H}]^T$ are the hydrodynamic terms, $\Phi = [\Phi_\mathrm{X} \quad \Phi_\mathrm{Y} \quad \Phi_\mathrm{K} \quad \Phi_\mathrm{N}]$ is the kinematic items in four DOF, $\mathbf{P} = [\mathbf{P}_\mathrm{X} \quad \mathbf{P}_\mathrm{Y} \quad \mathbf{P}_\mathrm{K} \quad \mathbf{P}_\mathrm{N}]^T$ is the corresponding parameters being identified in this study.

3. PSO based parameter estimation

Firstly introduced in [6], the PSO algorithm is proposed by imitating the animals' social behaviours, such as fish schooling, bees swarming and bird flocking. It is found that the PSO method is easy to be implemented as the system identification method in generating the high-quality solution considering its computationally inexpensive in the aspect of CPU burden and memory requirement of the computer [7].

The PSO is a method considering the individual evolutionary incorporated with companions' competition and cooperation. In more details, the individual, or namely the particle, of PSO is initialized with a random population and assigned with the dynamically alerted propagation velocity according to its own and swarm's experience. In use of this principle, these particles will search the space of the model and adjust the trajectory of each particle to approach their local best solutions (namely *lbest*), while optimizing the best solution by the global version of the whole swarm (namely *gbest*) at each generation. The PSO method is executed by changing the velocity of every particle to approach the lbest at each iteration and eventually converge the gbest. The flow chart to show the procedure of the PSO is shown in figure 2.

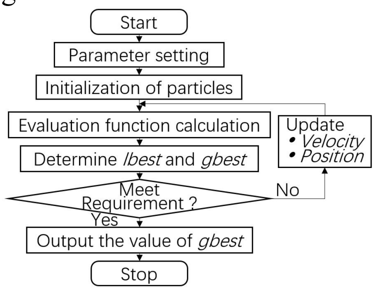

Figure 2. The PSO based algorithm for system identification.

The evaluation function is represented as:

$$E = \frac{1}{2}\sum_1^n (\mathbf{H}_{obs} - \Phi_{obs}\mathbf{P}_{SI})^2 \tag{3}$$

where n is the observation sampling number, $\mathbf{H}_{obs}$ and Φ_{obs} are the hydrodynamic and kinematic terms from observation and $\mathbf{P}_{SI}$ is a vector of the identified coefficients. The velocity of each particle in the current generation can be updated as:

$$V_i^{k+1} = \begin{cases} V_{min} & if\ V_i^{k+1} < V_{min} \\ V_{max} & if\ V_i^{k+1} > V_{max} \\ W \cdot V_i^k + c_1 \cdot r_1 \cdot (lbest_i - P_i^k) + c_2 \cdot r_2 \cdot (gbest_i - P_i^k) & other \end{cases} \tag{4}$$

where V is the evolve velocity of the particle, $[V_{min}, V_{max}]$ is the range to clamp the evolving speed of each particle, k is the sequence of generation, $i = 1,...,m$ is the indexing number of particle sets, w is the inertial factor, c_1 and c_2 are the constant coefficients standing for acceleration, r_1 and r_2 are independent random within the range of [0,1], P is the evolved position of the particles, which are used to optimizing the optimum of the solution. The value can be formulated as follows:

$$P_i^{k+1} = \begin{cases} P_{min} & if\ P_i^{k+1} < P_{min} \\ P_{max} & if\ P_i^{k+1} > P_{max} \\ P_i^k + V_i^{k+1} & other \end{cases} \tag{5}$$

where $[P_{min}, P_{max}]$ is the range to control the roaming space of the solutions.

Therefore, in use of the POS method, the parameter estimation problem can be formulated as the multi-objective function to minimize the error between the calculated data by using the estimated parameters and the experimental measured data. The procedure of the PSO based system identification process for the ship can be summarized as follows:

- Step 1: Clarify the rigid-body and hydrodynamic added parameters of the ship being identified; calculate the hydrodynamic force and moment on the ship's hull including *X*, *Y*, *K*, and *N*;
- Step 2: Set the initial parameters and particles in the first generation; develop the observation based input-output matrix for local and global evaluations functions;
- Step 3: Determine the *lbest* and *gbest* through the comparisons amongst the value of evaluation function at the current iteration;
- Step 4: Update the velocity and the position of each set of particles to optimize the best solution of the hydrodynamic parameters;
- Step 5: Output the *gbest* as the optimum for modelling when the stopping requirement is met, or conduct the Step 3 and 4.

4. Experimental application and results

To verify the reasonability of the proposed PSO method for the ship's modelling, a physical 1:100 scaled model of 'M/V P&O Nedlloyd Hoorn' is employed. The free-running vessel constitutes five modules: power supply, sensors kit, manoeuvring system, myRIO based onboard embedded computer as the real-time I/O platform, and the onshore computer with LabVIEW. More details about the main characteristics, the mechatronic scheme, as well as the data processing method for data acquisition of 'Hoorn' can be seen in [8]. In use of the free-running platform, the corresponding standard manoeuvring experiments, namely turning circle tests with $20°$ rudder angle (seen figure 3) as well as the $20° - 20°$ zig-zag tests, were carried out to acquire the experimental trails and attitudes.

Figure 3. The turning circle test of 'Hoorn' in open water with diameter at 5.7*L.

The experiments for data acquisition used for modelling were conducted with wind Beaufort-scale 1, which means that the environmental impact on the ship's stabilization can be ignored. The shaft speed of the ship is set at $900\,rpm$, the initial yaw angle is $10\,degrees$ and the initial roll angle is $0\,degree$. By using the proposed PSO method for the system identification, the hydrodynamic coefficients of the ship in the aspect of surge, sway, yaw and roll were optimized as shown in table 1.

Table 1. Identified hydrodynamic coefficients of the 'Hoorn' in four DOF.

Surge	Sway	Roll	Yaw
$X'_{uu} =- 0.0031$	$Y'_{v} =- 0.0468$	$K'_{v} = 0.0008$	$N'_{v} =- 0.0109$
$X'_{vr} =- 0.0023$	$Y'_{r} =- 0.0001$	$K'_{r} = 0.0002$	$N'_{r} =- 0.0045$
$X'_{vv} = 0.0142$	$Y'_{vvv} = 0.0248$	$K'_{p} = 0.0002$	$N'_{p} =- 0.0001$
$X'_{rr} = 0.0197$	$Y'_{vvr} =- 0.2533$	$K'_{vvv} =- 0.0265$	$N'_{vvv} = 0.0036$
$X'_{\phi\phi} = 0.0159$	$Y'_{vrr} =- 0.1259$	$K'_{vvr} =- 0.0080$	$N'_{rrr} = 0.0016$
	$Y'_{vv\phi} =- 0.0143$	$K'_{vrr} = 0.0096$	$N'_{vvr} =- 0.0227$
		$K'_{vv\phi} =- 0.0105$	$N'_{vrr} = 0.0012$
		$K'_{rr\phi} =- 0.0015$	$N'_{vv\phi} =- 0.0181$
			$N'_{v\phi\phi} =- 0.0058$
			$N'_{rr\phi} =- 0.0032$
			$N'_{r\phi\phi} = 0.0023$

To verify the rationality of the parameters optimized by the PSO method, these hydrodynamic coefficients incorporated with the maneuvering characteristics are used in the Equation (1) to develop the mathematical model, where the inputs consist of the rudder angle, propeller shaft speed, and the outputs consist of the trails and attitude of the ship. The simulated motions of the 'Hoorn' are iterated by solving the ordinary differential equations utilizing Bogacki-Shampine method in S-function, Simulink.

By using the above-mentioned mathematical model, the comparison between the experimental and simulated results are conducted. The simulations in $70\ s$ was executed to make the ship turning with rudder angle at $20\ degrees$ and with initial speed at $1.25\ m/s$. The trajectories of turning circles about $840\ degrees$ in figure 4 indicate that the simulated results meet the experimental observation well.

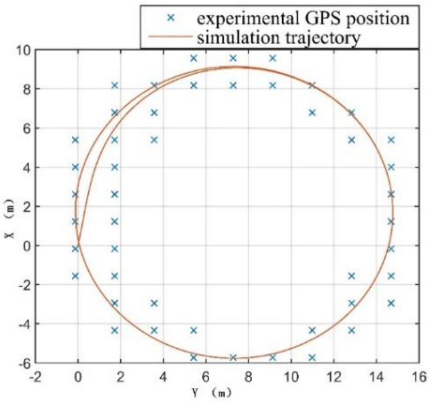

Figure 4. Trajectory measured in turning circle test with free-running ship and simulation.

In addition, the same conclusion also can be drawn from the roll angles in figure 5 and yaw angles in figure 6. Although there exists a slight deviation between experimental and simulated roll angle, the initial differences can be explained as the environmental impacts of instantaneous wind around the experiment spot which lead to the measurement drifting. Moreover, the difference is acceptable since the results after 10 s, which means the turning motion is stable, show that the two kinds of results have a high agreement with each other.

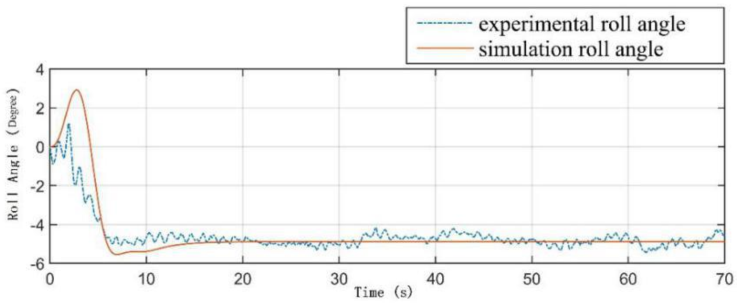

Figure 5. Roll angle measured in turning circle test with free-running ship and simulation.

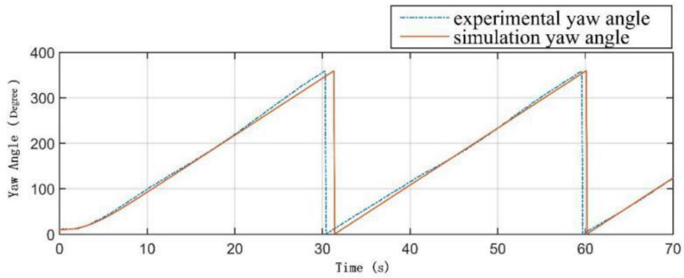

Figure 6. Yaw angle measured in turning circle test with free-running ship and simulation.

According to the comparison, it is found that the model is capable of representing the ship's motions. Therefore, the proposed PSO method for ship's modelling is demonstrated to be qualified in optimize the hydrodynamic coefficients with adequate accuracy.

5. Conclusion

From the perspective of modelling, the development of the ship's mathematical model in motions is formulated into the system identification problem to estimate the best solutions of the hydrodynamic coefficients. The novel PSO algorithm was utilized to find the global optimum of each parameter. The comparison between experimental data from real ship and simulation data from the mathematical model demonstrated that the effectiveness, efficiency and robustness of the PSO based system identification algorithm. Future work will focus on the investigation of the modelling by using multi sensors and considering huge environmental disturbance to develop the ship's mathematical model in different sea states.

Acknowledgements

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