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The optimal route planning for inspection task of autonomous underwater vehicle composed of MOPSO-based dynamic routing algorithm in currents

Yu-Hsien Lin[a,b,*], Lin-Chin Huang[a], Shao-Yu Chen[a], Chao-Ming Yu[a]

[a] Dept. of Systems & Naval Mechatronic Eng., National Cheng-Kung University, Tainan City 70101, Taiwan
[b] Research Center of Energy Technology and Strategy, National Cheng-Kung University, Tainan City 70101, Taiwan

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ABSTRACT

For supporting the dynamic routing plan more efficiently, this study has been established by integrating PSO (Particle Swarm Optimization) −based dynamic routing algorithm, self-tuning fuzzy controller, a stereo-vision detection technique and 6-DOF mathematical model into the inspection system of AUV (Autonomous Underwater Vehicle). Specifically, the PSO-based dynamic routing algorithm is modified by adopting the concept of Multi-Objective Particle Swarm Optimization (MOPSO), which is able to handle different weights of objectives in parallel. Therefore, a modular structure is applied to program design of the system by using the graphical language, LabVIEW®, which is composed of 6-DOF motion module, a self-tuning fuzzy control module, a stereo-vision detection module, and a dynamic routing module. Performances resulted from the MOPSO-based dynamic routing algorithm would be discussed by conducting a series of inspection tasks in the imitated offshore wind farm. Additionally, selections of fixed weight and dynamic weight of MOPSO-based dynamic routing algorithm would be compared via Pareto frontiers for feasible solutions of both sailing time and energy consumption. Eventually, it is verified that the MOPSO-based dynamic routing algorithm in our system is not only able to estimate the feasible routes intelligently, but also identify features of underwater structures for the purpose of positioning.

1. Introduction

In this study, a fuzzy control system, 6-DOF mathematical model, image detection scheme can be integrated into an AUV for navigation. Firstly, the fuzzy theorem [1] has been used to transform a value to a corresponding function that describes the level of the value. This is useful for solving logically uncertain problems. To reduce the unpredictability in AUV motion, a fuzzy control system [2] was applied to speed control and depth control. Moreover, DeBitetto [3] applied the nonlinear fuzzy theory to the ballast system of an AUV for depth control. Fang et al. [4] proposed and verified a self-tuning fuzzy controller as a useful searching technique to help the AUV avoid obstacles.

In the field of inspection, image sonar systems are widely used in AUVs. A method suggested by [5] is able to match side-scan sonar images to those in a reference database for navigation. In addition, image sonar systems should be operated at relatively low frequencies to obtain long-range data [6]. Since image sonar systems are expensive and not widely available, the use of vision-based systems is thus suggested. Foresti [7] presented a vision-based system for inspection of underwater structures composed of pipelines and cables. Ortiz et al. [8] verified that an underwater cable and its direction can be tracked using a vision-based system. Furthermore, visual imagery has been applied for detecting environments and navigating an AUV around a fixed path [9].

To solve the path-planning problem, an optimization method, Particle Swarm Optimization (PSO), was originally attributed to J. Kennedy [10] based on the foraging behavior of birds. Onwunalu and Durlofsky [11] applied PSO to optimally search for oil and gas. In order to improve particle dynamics, linearly-decreasing inertia weight, random inertia weight, and dynamic inertia weight have been proposed [12,13]. The Multipoint Potential Field (MPPF) method [14] was adopted to calculate relationships among detected points, obstacles, and the optimal course. For processing multi-objective problems, Zhang et al. [15] applied multi-objective particle swarm (MOPSO) algorithm to robot navigation, including degree of risk and path distance. The simulation results demonstrated that MOPSO can generate optimal paths by using high-quality Pareto fronts. Besides, the multi-objective NSGA-II algorithm [16] was used to optimize total path length, safety margin, smoothness of planar motion, and diving gradient by adopting Pareto fronts. It was suggested that optimized routing of a ship can be

* Corresponding author at: Dept. of Systems & Naval Mechatronic Eng., National Cheng-Kung University, Tainan City 70101, Taiwan.
E-mail address: vyhlin@mail.ncku.edu.tw (Y.-H. Lin).

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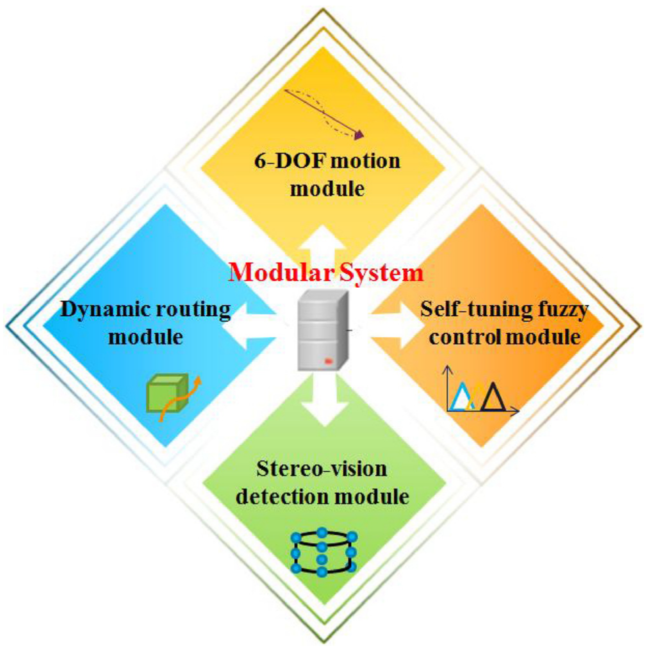

Fig. 1. The schematic diagram of the modular system.

selected dynamically by applying the three-dimensional modified isochrone (3DMI) method [17] [18].

For processing multi-objective problems, the weighted-objective aggregation approach [19], lexicographic ordering approach [20], non-Pareto vector-evaluated method [21], Pareto-based dominance method [22] were suggested. The optimal solution can be obtained by distributing weights among all objective functions. Generally, fixed weight must be specified using a priori knowledge. On the other hand, dynamic weight [23], including Linear Weighted Aggregation (LWA), Bang-bang Weighted Aggregation (BWA) and Sinusoidal Weighted Aggregation (SWA), is adjustable. Zhang [24] applied Multiple Particle Swarm Optimization with Inertia Weight (MPSOIW) and verified that LWA is able to acquire results stably.

In this study, the weighted-objective aggregation approaches, *i.e.* fixed weight and dynamic weight, are adopted for processing multi-objective problems of time and energy consumption. The influences of ocean currents on performances of the AUV under different sailing velocities by means of MOPSO-based dynamic routing algorithms would be realized. The contents of this manuscript will be introduced in the following sections.

2. The structure of modular system

The modular system is programmed by LabVIEW®, consisting of four modules, *i.e.* 6-DOF motion module, self-tuning fuzzy control module, stereo-vision detection module and dynamic routing module, as illustrated in Fig. 1. The details and fundamental theories of these modules would be introduced in the following sections.

2.1. Six-dof motion module

2.1.1. Coordinate systems

In order to define orientation and motion responses of AUV, the earth coordinate system, *o-xyz*, and the body-fixed coordinate system, o_b-$x_b y_b z_b$, are indicated in Fig. 2. It is found that the positive z-axis is directed downward, whereas o_b is denoted as the center of gravity of the AUV. Additionally, three translational displacements of surge, sway and heave are defined by x, y, z; whereas three rotational displacements of roll, pitch and yaw are denoted as ϕ, θ and ψ, respectively. It is noted that the rotational displacements of ϕ, θ and ψ are along the x-, y- and z-axes in order. The translational velocities of surge, sway and heave are represented by u, v and w; whereas the angular velocities of roll, pitch and yaw are denoted as p, q and r, respectively. For more details, 6-DOF variables are listed in Table 1.

2.1.2. Six-DOF motion equations

In the 6-DOF motion module, the equations include inertia, added mass, hydrodynamic damping, gravity, buoyancy and thruster forces, which are given by Eqs. (1)–(6) [4]. Each motion equation would be introduced in the following:

1. Surge:

$$\begin{aligned}(m - X_{\dot{u}})\dot{u} + mz_G\dot{q} - my_G\dot{r} = {} & -mp(y_G q + z_G r) + (mx_G q - mw + Z_{\dot{w}}w)q \\ & + (mx_G r + mv - Y_{\dot{v}}v)r + (X_u + X_{u|u|}|u|)u \\ & - (W-B)\sin\theta + F_{Tx} + F_{Cx}\end{aligned} \quad (1)$$

2. Sway:

$$\begin{aligned}(m - Y_{\dot{v}})\dot{v} + mz_G\dot{p} - mx_G\dot{r} = {} & -p(my_G q + mw - Z_{\dot{w}}w) - mq(z_G r + x_G p) \\ & + (my_G r - mu - X_{\dot{u}}u) r + (Y_v + Y_{V|V|}|V|) v \\ & + (W - B)\cos\theta\sin\varnothing + F_{Ty} + F_{Cy}\end{aligned} \quad (2)$$

3. Heave:

$$\begin{aligned}(m - Z_{\dot{w}}) w + my_G\dot{p} - mx_G\dot{q} = {} & p(mz_G q - mv + Y_{\dot{v}}v) + q(mz_G q + mu - X_{\dot{u}}u) \\ & - mr(x_G p + y_G q) + (Z_w + Z_{w|w|}|w|) w \\ & + (W - B)\cos\theta\cos\varnothing + F_{Tz}\end{aligned} \quad (3)$$

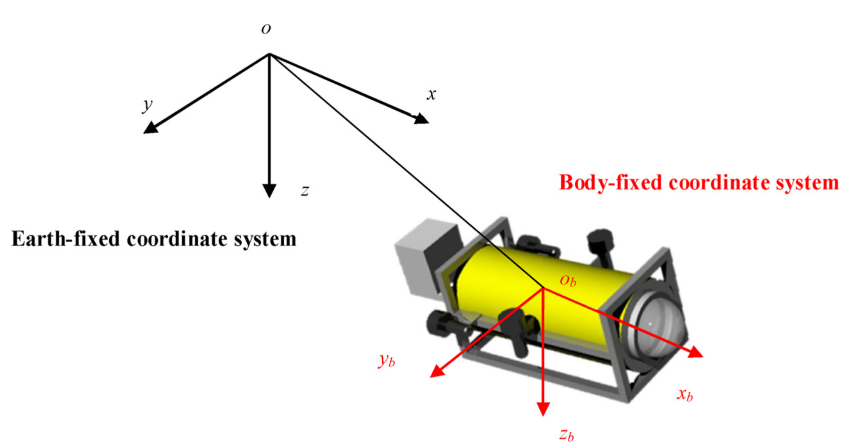

Fig. 2. Earth and body-fixed coordinate systems.