Ocean Engineering 118 (2016) 216–226

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

An energy optimal thrust allocation method for the marine dynamic positioning system based on adaptive hybrid artificial bee colony algorithm

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ARTICLE INFO

Article history:
Received 29 May 2015
Received in revised form
21 March 2016
Accepted 5 April 2016

Keywords:
Thrust allocation
Adaptive hybrid artificial bee colony algorithm
Particle swarm optimization
Chaotic search
Differential evolution

ABSTRACT

Thrust allocation (TA) is an important part in dynamic positioning systems (DPS). The function of TA is to allocate the thrust and angle of each thruster so that the desired force and moment can be achieved. Based on our previous work, an adaptive hybrid artificial bee colony algorithm with chaotic search (AHABCC) is proposed in this study. This algorithm introduced a mutation operator from differential evolution (DE) and the social cognitive part of particle swarm optimization (PSO) to the honeybee and chaotic search strategies to scouts searching. The proportion of each search strategy selected is dynamically adjusted to achieve the optimization. Therefore, the AHABCC can automatically switch the search strategy for different bee colonies. The optimal search of AHABCC is faster compared to HABCC, and the probability of obtaining optimal results and avoiding local optimums is significantly increased. In addition, the power consumption of AHABCC is less than that of HABCC. The effectiveness of the AHABCC algorithm is demonstrated using simulations.

1. Introduction

Marine dynamic positioning system (DPS) has been widely employed in many floating vessels/platforms in the sea and is an important support technology for exploration and exploitation of oceanic resources. A DPS mainly consists of a position measurement system, control system, thrust allocation (TA) system and propulsion system (Sorensen, 2011). It is known that vessels/platforms equipped with a DPS use thrusters and main propellers to produce a desired thrust via azimuth/tunnel thrusters, as well as to control maneuvering. Thrust can compensate for environmental forces acting on the vessel/platform to maintain position and head as closely as required to some desired position in the horizontal plane. There are several types of thrusters, namely tunnel thrusters, azimuth thrusters, aft rudders, stabilizing fins, control surfaces and so on (Fossen, 2002). Generally speaking, tunnel and azimuth thrusters are the most widely used thrusters in DPS. However, DPS have three equations that include a longitudinal force, a lateral force, and a moment requirement from the control system to be satisfied. The task of a thrust system is to allocate the force/angle commands to each thruster so that the desired force and moment from control system can be achieved. Therefore, there have three different situations when comparing the control input and vessel degree-of-freedom, namely under-actuated, fully-actuated and over-actuated. It was noted in (Rindarøy and Johansen, 2013) that most of the dynamic positioning (DP) vessels are over-actuated. Therefore, the over-actuated vessel with DPS is considered in this study. Then, the TA problem is usually formulated as an optimization problem with some constraints. The main constraints (Johansen et al., 2004), or optimization objectives, of DPS are the handling and compensating thruster failures, minimizing fuel consumption, minimizing thruster wear, accounting for thruster losses of various types, and handling problems when required power is not available.

The solutions for TA optimization problems were widely studied. When the desired forces are provided by thrusters in fixed directions alone or in combination with rudders and control surfaces, then the TA problem can be considered as an unconstrained least-squares optimization problem and an explicit solution can be obtained (Fossen and Sagatun, 1991; Fossen, 1994). If the thruster limitations are taken into account, then the TA problem becomes a constrained optimization problem, several methods are proposed to solve this type of problem. For instance, Johansen et al. (2005,

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http://dx.doi.org/10.1016/j.oceaneng.2016.04.004
0029-8018/

2003) proposed an explicit solution for parametric quadratic programming (QP) to marine vessels and an extension of the mp-QP algorithm respectively. Sørdalen (1997) proposed an iterative solution to solve the QP problem.

When the vessel is equipped with azimuth thrusters, then the TA problem generally becomes a *non-convex nonlinear* optimization problem. Liang and Cheng (2004) proposed an optimum control of a thruster system using the sequential quadratic method. Wit (2009) selected the thrust and azimuth direction of the thrusters as design variables for the optimization problem, and the QP algorithm was used to solve the problem. It should be noted that there is a tradeoff between energy consumption and maneuverability of dynamically positioned vessels. Johansen et al. (2004) proposed a TA optimization objective function via adding a term to avoid singular configurations and Sequential Quadratic Programming (SQP) was employed to find the TA solution. The advantages of aforementioned QP and SQP methods are real-time implementation and strong local optimization ability. However, the global optimization ability is comparatively weak. Therefore, several TA solutions based on intelligent computation techniques were presented. For instance, Dawei et al. (2010) proposed a TA solution based on a genetic algorithm (GA) (Yanduo and Jing, 2007). The presented method is effective and validated via simulation results. Parikshit (2013) also proposed a method based on ITHS (Intelligent Tuned Harmony Search) to solve TA problem. Zhao and Myung-IlRoh (2015) proposed a hybrid optimization algorithm based on GA and SQP algorithm to solve TA problem. However, the convergence speed of such methods still needs to be further improved when it is employed in DPS.

As an intelligent computation technique, an artificial bee colony (ABC) (Karaboga, 2005) algorithm simulates the intelligent foraging behavior of honey bee swarms. It is a very simple, robust and population-based stochastic optimization algorithm. ABC has been employed to solve many problems (Karaboga et al., 2007; Karaboga, 2009; Apalak et al., 2014). However, ABC algorithms are premature and their speed of convergence needs to be further improved. For instance, Singh (2009) presented a new ABC algorithm to the leaf-constrained minimum spanning tree problem. Pei-Wei et al. (2009) presented an enhanced ABC optimization with the formula of gravitation. However, when an ABC is applied to a TA problem, the improved algorithm should consider the unique problem characteristics.

Besides aforementioned GA and ABC, there are several intelligent optimization algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE) and Biogeography-based Optimization (BBO) and so on. Hybrid intelligent optimization algorithms have the advantages of avoiding local minimums and speeding up the convergence rate compared with single intelligent optimization method, for instance hybrid PSO and DE (Liu et al., 2010), hybrid ACO and DE (Ying-Pin, 2010), hybrid BBO and PSO (Guo et al., 2014). However, the adaptive switch of different search mechanisms in different algorithms is rarely raised. In our previous work (Wu et al., 2014), a mutation operator from differential evolution (DE) and the social cognitive part of particle swarm optimization (PSO) were introduced to the honeybee search strategy. Therefore, the probability of finding optimal results and avoiding local optimums is significantly increased. The proposed algorithm is called the hybrid artificial bee colony with chaotic search (HABCC). However, changing different search strategies for bees in HABCC is based on the manual setting of the iteration number. Therefore, it is necessary to further develop HABCC into an adaptive hybrid artificial bee colony with chaotic search (AHABCC) algorithm. The AHABCC can automatically switch the search strategy for different bees. One of the advantages for AHABCC is that it does not require a manual setting of the iteration number, making it much more practical for engineering application. Another advantage is that the AHABCC can fully utilize the merits of DE and PSO, as the switch search strategy can switch automatically based on the performances of different search strategies.

The rest of this paper is organized as follows. In Section 2, the TA mathematical model for one type of pipe-laying crane vessels is presented to lay a basis for the following development. In Section 3, the basic artificial bee colony algorithm is introduced and analysed for further development. In Section 4, an adaptive hybrid artificial bee colony algorithm is proposed and the procedure is also given. In Section 5, a comparison experiment is conducted to verify the feasibility and effectiveness of AHABCC over the other three algorithms including HABCC, ABC and SQP. Our concluding remarks and future work are contained in the final section.

2. Thruster allocation mathematical model

In this study, the mathematical model of thruster allocation is based on a pipe-laying crane vessel with a DPS equipped with seven azimuth thrusters. The arrangement of the propellers is shown in Fig. 1.

In this section, the mathematical model of thruster allocation in DPS is introduced to lay a basis for finding the solution. Due to the capacity constraints of the propulsion system, the optimization objective function (Johansen et al., 2004) of thrust allocation can be formulated as follows:

$$\min J(\alpha, F, s) = PW + s^T Qs + (\alpha - \alpha_0)^T \Omega (\alpha - \alpha_0) + \frac{\delta}{\varepsilon + \det(B(\alpha)B'(\alpha))} \quad (1)$$

Subject to the constraints (Rindarøy and Johansen, 2013; Johansen et al., 2004):

$$s = \tau - B(\alpha)F \quad (2)$$

$$F_{min} \le F \le F_{max} \quad (3)$$

$$\Delta F_{min} \le F - F_0 \le \Delta F_{max} \quad (4)$$

$$\alpha_{min} \le \alpha \le \alpha_{max} \quad (5)$$

$$\Delta\alpha_{min} \le \alpha - \alpha_0 \le \Delta\alpha_{max} \quad (6)$$

where W is the total power consumption in the first term, combining the power consumption of the individual thrusters and P is the weight factor. In the second term, s is the error between the commanded and achieved generalized force. Q is the matrix of the diagonal weights. The $s^T Qs$ penalizes the error s between the commanded and achieved generalized force. τ is commanded generalized force. $B(\alpha)$ is the control allocation matrix. F is the thrust force provided by thrusters. F_{min} and F_{max} are the minimum

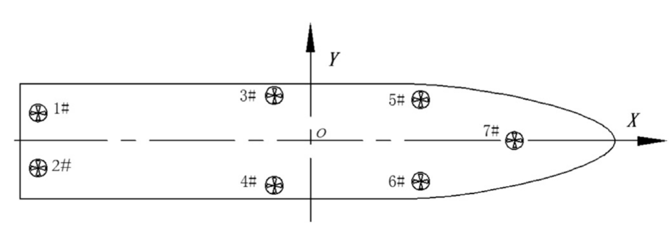

Fig. 1. Thruster layout of the vessel with DPS.