MPC-based Motion Planning and Control Enables Smarter and Safer Autonomous Marine Vehicles: Perspectives and a Tutorial Survey

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***Abstract*—Autonomous marine vehicles (AMVs) have received considerable attention in the past few decades, mainly because they play essential roles in broad marine applications such as environmental monitoring and resource exploration. Recent advances in the field of communication technologies, perception capability, computational power and advanced optimization algorithms have stimulated new interest in the development of AMVs. In order to deploy the constrained AMVs in the complex dynamic maritime environment, it is crucial to enhance the guidance and control capabilities through effective and practical planning, and control algorithms. Model predictive control (MPC) has been exceptionally successful in different fields due to its ability to systematically handle constraints while optimizing control performance. This paper aims to provide a review of recent progress in the context of motion planning and control for AMVs from the perceptive of MPC. Finally, future research trends and directions in this substantial research area of AMVs are highlighted.**

***Index Terms*—Autonomous marine vehicles (AMVs), model predictive control (MPC), motion control, motion planning.**

I. Introduction

IN recent years, there has been an increasing demand to use cutting-edge technology and advanced equipment to explore and exploit the ocean for broad applications, including deep sea observations, marine gas detection, search and rescue (both onshore and offshore), and inspection and maintenance [1]. Consequently, these maritime applications have stimulated research interests in developing advanced marine mechatronic systems that integrate mechanics, electronics, and control algorithms [2]. In the past two decades, autonomous marine vehicles (AMVs) as a typical representative of marine mechatronic systems, including remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), autonomous surface vehicles (ASVs), and underwater robotic vehicles (URVs) have demonstrated exceptional success in a wide range of marine activities, as shown in Fig. 1. The success of AMVs is mainly due to their superior abilities to execute increasingly challenging and complex missions at sea. Despite the advances in this field, smarter motion planning and control approaches are still needed to enhance AMVs' autonomy, effectiveness, safety, and reliability under challenging operating conditions, such as communication failure, confined waterways, and unfavorable weather conditions. It should be noted that these AMV systems generally have the following features or objectives:

1) Complex nonlinear systems are subject to physical constraints, e.g., control input and system state constraints;

2) It is desired to explicitly improve the control performance of AMVs under uncertainties and complex environments;

3) It is desired to enhance the reliability, safety and flexibility, extend the operational range, enhance autonomy, as well as reduce operating costs.

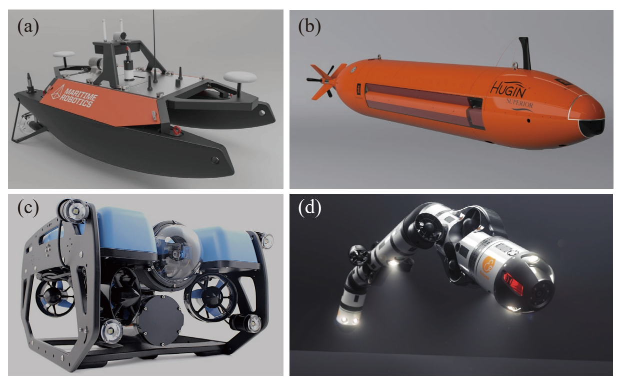

Fig. 1. Four representative types of AMVs: (a) ASV, the Otter ASV [3]; (b) AUV, the Hugin AUV [4]; (c) ROV, the BlueROV2 [5]; (d) URV, the Eelume underwater robot [6].

Noticeable motion planning and control methods have been developed for AMVs [2], [7], [8]. Among these algorithms, model predictive control (MPC, also known as receding horizon control) is a well-established control scheme for broad applications such as robotic systems, and it has distinct capabilities to deal with physical constraints, with multiple inputs and multiple outputs while optimizing the control performance [9], [10]. At each time step, an online constrained optimization problem is solved based on the current measurement, and the first element u_0^* of a finite optimal control input sequence $\{u_0^*, u_1^*, \ldots, u_{T-1}^*\}$ is applied to the actual system. In practice, however, the high computational demands of solving the online optimal control problem have limited its appli-

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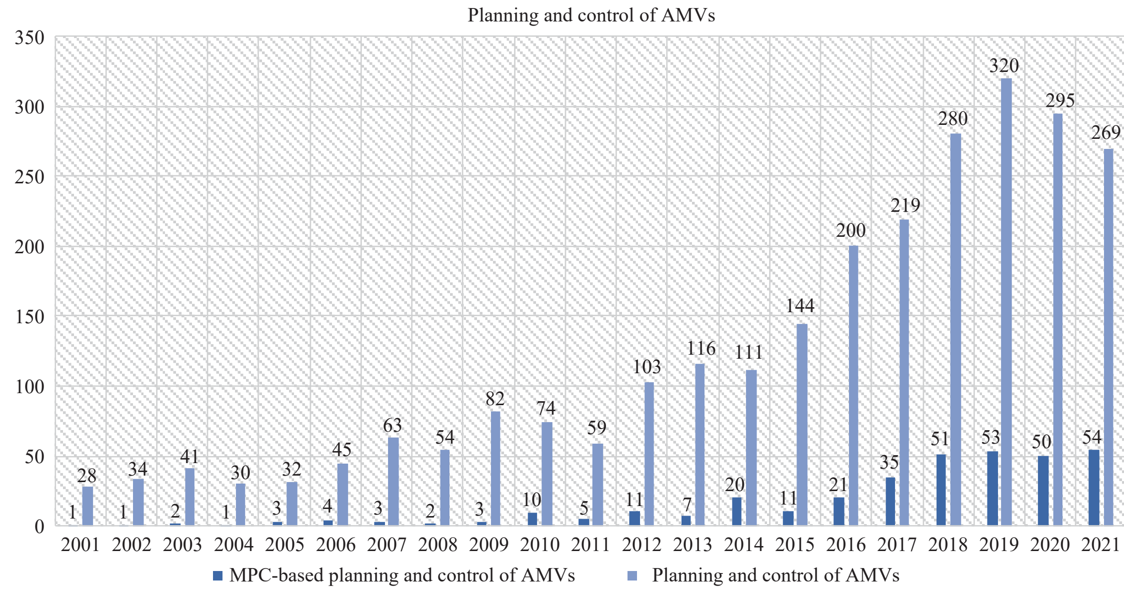

Fig. 2. Number and trend of published articles on "MPC-based planning and control of AMVs" and "Planning and control of AMVs" indexed in the Web of Science (WOS) since 2001. Source: WOS.

cations to the cases where onboard computational resources are inadequate, and dynamics are slow such as process control. The recent developments of the increasing computational power and optimization techniques provide the opportunity for MPC to be deployed in the maritime applications with limited onboard computational resources or fast dynamics such as unmanned aerial vehicles (UAVs) [11] and automated vehicles [12]. In particular, MPC-based motion planning and control approaches present huge potential for enabling smarter and safer operations of constrained AMVs in complex environments.

Planning and control of AMVs has received increasing attention during the last two decades, as shown in Fig. 2. The published papers in this area are selected from *Web of Science* (WOS) with the following keywords in the title: "autonomous marine vehicle/AMV", " autonomous surface vehicle/ASV", " remotely operated vehicle/ROV", "autonomous underwater vehicle/AUV", "planning and control", and "model predictive control/MPC". It is worth mentioning that the information provided by the WOS illustrates a rising research trend in the topics of motion planning and control of AMVs from 2001 to 2021.

Regarding AMV applications, several papers have been published for reviewing a specific research topic, such as [15] for dynamic control, [16], [20], [26] for planning, [22] for collision avoidance, and [8], [21] for ASV; see Table I for more details. The last two decades have witnessed emerging activities in MPC for the autonomous intelligent mechatronic systems [10]; these systems generally have fast dynamics and limited computational resources. The field of advanced control/planning and AMVs is vast, and we would like to provide a comprehensive overview of recent research efforts in the motion planning and control for AMVs from the perspective of MPC in this survey.

The remainder of this paper is structured as follows. In Section II, we describe the mathematical model of the AMV system. Section III-A reviews the MPC-based motion planning algorithms for AMVs, whereas Section IV surveys the state of the art for MPC algorithms for motion control of AMVs, including dynamic positioning control, trajectory tracking control, path following control and cooperative control. Section V presents some future directions for the AMVs' motion planning and control area. Some concluding remarks are found in Section VI. The organization of this survey is illustrated in Fig. 3.

Notations: The symbol $\mathbb{R}_{\geq 0}$ represents the set of nonnegative real numbers. Let $\mathbb{R}^n$ represent the n-dimensional Euclidean space, and $\mathbb{R}^{m\times n}$ represent the set of all $m\times n$ real matrices. For $x\in\mathbb{R}^n$, $\|\cdot\|$ denotes the Euclidean norm, $\|x\|_P=\sqrt{x^TPx}$ represents the weighted Euclidean norm, in which P is positive definite. The superscript "T" represents the transposition. The states $x(s|t)$ and $x(t)$ denote the predicted system state at future time $t+s$ determined at time t and the actual system state x at time t, respectively. Some notations of AMVs are provided in Table II.

II. Modeling

The mathematical model of AMVs introduced in this section is employed as the foundation for model-based motion planning/control design and analysis [7]. For the motion description of AMVs, the body-fixed frame $\{b\}$ and the global coordinate frame $\{n\}$ are defined. As shown in Fig. 4, six independent coordinates are used to show the position and orientation of the AMVs moving in six degrees of freedom (DOF). The six motion components of AMVs in 6-DOF are typically defined as surge, sway, heave, roll, pitch and yaw.

A. 6-DOF Model for AMVs

Linear Velocity Transformation: The zyx-convention from $\{n\}$ to $\{b\}$ customarily describes the Euler angle rotation matrix $R_b^n(\Theta)$ with the argument Θ

$$R_b^n(\Theta)=R_{z,\psi}R_{y,\theta}R_{x,\phi} \tag{1}$$

with respect to

TABLE I
SOME EXISTING SURVEYS/REVIEWS ON MOTION PLANNING AND CONTROL OF AMVS

Ref	Author, Year	Focus	Brief description
[13]	Roberts, G., 2008	Unmanned marine vehicles, control	This paper discusses early developments in ship control and unmanned underwater vehicle operation mainly from a control viewpoint.
[14]	Manley, J. E., 2008	USVs	The review of enabling technologies for USVs.
[15]	Sørensen, A. J., 2011	Marine systems, dynamic positioning	The survey provides a comprehensive overview of dynamic positioning (DP) control algorithms for marine systems.
[16]	Campbell, S., *et al.*, 2012	USVs, GNC*, collision avoidance	This review discusses the research of USV collision avoidance in terms of the planning and control with respect to the international regulations for avoiding collisions at Sea (COLREGs).
[8]	Liu, Z., *et al.*, 2016	USVs, GNC	This paper provides an overview of recent advances in USVs, focusing primarily on different GNC methods.
[2]	Shi, Y., *et al.*, 2017	Marine systems, control	This paper surveys the progress in the controllers of the marine mechatronic systems, such as AMVs, wave energy converters, offshore wind turbines, and profiling floats.
[17]	Melo, J., *et al.*, 2017	AUVs, navigation	This survey offers an overview of different navigation techniques for AUVs, such as terrain-based navigation methods.
[1]	Zereik, E., *et al.*, 2018	Marine robotic applications	This paper presents several representative projects, some emerging challenges and potential research trends in the field of marine robotics.
[18]	Sahoo, A., *et al.*, 2019	AUVs, GNC	The review summarizes the developments of AUVs with different research aspects such as mechanical design, control, navigation, localization, planning and communication.
[19]	Huang, Y., *et al.*, 2020	Ships, collision avoidance	This paper introduces an overview of collision avoidance techniques used for human-operated and autonomous ships.
[20]	Zhou, C., *et al.*, 2020	ASVs, planning	This paper presents the progress of path planning methods for ASVs. Based on multi-modality constraints, these methods are classified into three types: route, trajectory and motion planning.
[21]	Chen, L, *et al.*, 2020	Vessels, cooperative control	This paper provides an overview of distributed control algorithms for waterborne transport systems. Ultimately, a hierarchical control scheme is presented for the cooperative vessels.
[22]	Zhang, X., *et al.*, 2021	ASV, collision avoidance navigation	This paper surveys some advances in collision avoidance technologies for ASVs from scientific research to transportation.
[23]	Gu, N., *et al.*, 2022	AMVs, LOS guidance	This paper provides an overview of the development in line-of-sight (LOS) guidance for the path following of a single AMV and multiple AMVs.
[24]	Gu, N., *et al.*, 2022	AMVs, observer	This paper summarizes the existing disturbance estimation approaches, including the extended state observers and the disturbance observers for AMVs.
[25]	Zhou, Z., *et al.*, 2022	URVs, cooperative and formation control	This paper reviews cooperative control methods for multiple underwater robots. The cooperation among robots is categorized depending on the measurement, the motion, and the task space.

* Guidance, navigation and control.

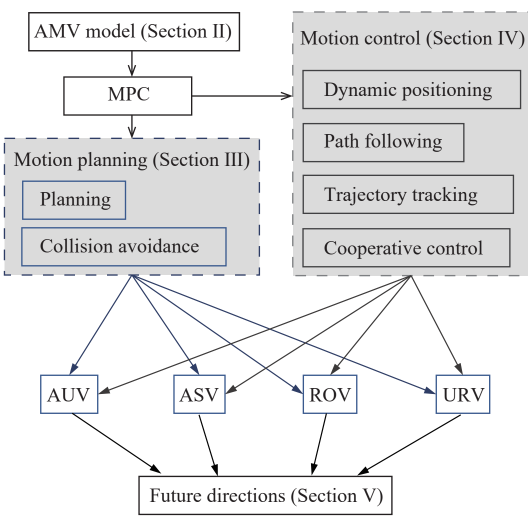

Fig. 3. Organization of this paper.

TABLE II
THE NOTATION OF AMVS

Symbol	Definition
$p^n=[x,y,z]^T$	The distance from NED to BODY in $\{n\}$
$\Theta=[\phi,\theta,\psi]^T$	The Euler angles, roll ϕ, pitch θ and yaw ψ
$\eta=[p^n,\Theta]^T$	The position and orientation vector
$v^b=[u,v,w]^T$	The body-fixed linear velocity
$\omega^b=[p,q,r]^T$	The body-fixed angular velocity
$\nu=[v^b,\omega^b]^T$	The linear and angular velocity in $\{b\}$
$f^b=[X,Y,Z]^T$	The body-fixed forces in $\{b\}$
$m^b=[K,M,N]^T$	The body-fixed moments in $\{b\}$
$\tau=[f^b,m^b]^T$	The forces and moments acting on AMVs
$X_{\dot{u}},Y_{\dot{v}},N_{\dot{r}}$	The added mass
X_u,Y_v,N_r	The linear damping coefficients
$X_{u\lvert u\rvert},Y_{v\lvert v\rvert},N_{r\lvert r\rvert}$	The second-order damping coefficients
$C(\nu)$	The Coriolis and centripetal matrix
$D(\nu)$	The damping matrix
$g(\eta)$	The gravitational/buoyancy forces and moments

$$R_{x,\phi}=\begin{bmatrix}1&0&0\\0&c\phi&-s\phi\\0&s\phi&c\phi\end{bmatrix},\ R_{y,\theta}=\begin{bmatrix}c\theta&0&s\theta\\0&1&0\\-s\theta&0&c\theta\end{bmatrix}$$

$$R_{z,\psi}=\begin{bmatrix}c\psi&-s\psi&0\\s\psi&c\psi&0\\0&0&1\end{bmatrix}$$

with $s\cdot=\sin(\cdot), c\cdot=\cos(\cdot)$. Expanding (1) yields

$$R_b^n(\Theta)=\begin{bmatrix}c\psi c\theta&c\psi s\theta s\phi-s\psi c\phi&c\psi c\theta s\phi+s\psi s\phi\\s\psi c\theta&s\psi s\theta c\phi+c\psi c\phi&s\psi s\theta c\phi-c\psi s\phi\\-s\theta&c\theta s\phi&c\theta c\phi\end{bmatrix}.$$

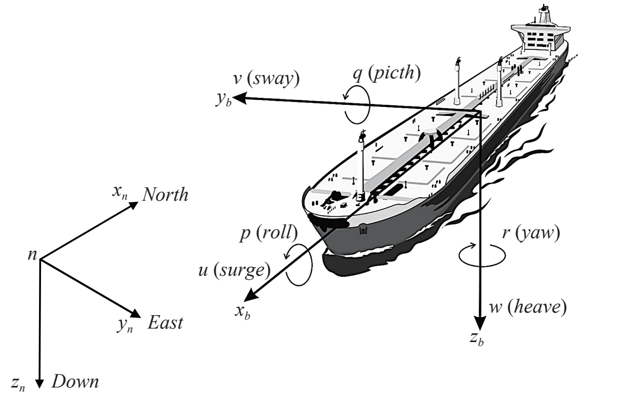

Fig. 4. Global coordinate frame $\{n\} = (x_n, y_n, z_n)$ and body-fixed frame $\{b\} = (x_b, y_b, z_b)$ [7].

Let v^n denote the linear velocity in the frame $\{n\}$. Then the body-fixed velocity v^b is expressed in $\{n\}$ as

$$v^n = R_b^n(\Theta)v^b \tag{2}$$

with $v^n = \dot{p}^n$.

1) Angular Velocity Transformation: The body-fixed angular velocity ω^b and the Euler angle rate $\dot{\Theta} = [\dot{\phi}, \dot{\theta}, \dot{\psi}]^T$ are related by the transformation matrix $T(\Theta)$

$$\dot{\Theta} = T(\Theta)\omega^b \tag{3}$$

in which

$$\omega^b = \begin{bmatrix}\dot{\phi}\\0\\0\end{bmatrix} + R_{x,\phi}^T\begin{bmatrix}0\\\dot{\theta}\\0\end{bmatrix} + R_{x,\phi}^T R_{y,\theta}^T\begin{bmatrix}0\\0\\\dot{\psi}\end{bmatrix}. \tag{4}$$

Expanding (4) we get

$$T(\Theta) = \begin{bmatrix}1 & \mathrm{s}\phi\mathrm{t}\theta & \mathrm{c}\phi\mathrm{t}\theta\\ 0 & \mathrm{c}\phi & -\mathrm{s}\phi\\ 0 & \mathrm{s}\phi/\mathrm{c}\theta & \mathrm{c}\phi/\mathrm{c}\theta\end{bmatrix}$$

with $\mathrm{t}\cdot = \tan(\cdot)$. Combining (2) and (3), we have the 6-DOF kinematic equations of AMVs

$$\dot{\eta} = \begin{bmatrix}\dot{p}^n\\ \dot{\Theta}\end{bmatrix} = \begin{bmatrix}R_b^n(\Theta) & \mathbf{0}_{3\times3}\\ \mathbf{0}_{3\times3} & T(\Theta)\end{bmatrix}\begin{bmatrix}v^b\\ \omega^b\end{bmatrix} = J(\eta)\nu. \tag{5}$$

2) Simplified Rigid-Body Dynamics: The center of gravity is assumed to coincide with the origin of the body-fixed frame $\{b\}$. The rigid-body dynamics of AMVs can be derived [27]

$$M_{RB}\dot{\nu} + C_{RB}(\nu)\nu = \tau \tag{6}$$

where $\tau = [X, Y, Z, K, M, N]^T$ denotes the propulsion forces. The rigid-body inertia matrix M_{RB} is simplified as

$$M_{RB} = \begin{bmatrix}m\mathbf{I}_{3\times3} & \mathbf{0}_{3\times3}\\ \mathbf{0}_{3\times3} & \mathbf{I}_g\end{bmatrix} \tag{7}$$

where m is the mass of the AMV, $\mathbf{I}_g$ is the inertia matrix

$$\mathbf{I}_g = \begin{bmatrix}I_x & 0 & 0\\ 0 & I_y & 0\\ 0 & 0 & I_z\end{bmatrix} \tag{8}$$

with I_x, I_y and I_z being the moments of the inertia about the x_b, y_b and z_b axes. The rigid-body Coriolis and centripetal matrix C_{RB} is

$$C_{RB}(\nu) = \begin{bmatrix}\mathbf{0}_{3\times3} & -mS(v^b)\\ -mS(v^b) & -S(\mathbf{I}_g\omega^b)\end{bmatrix} \tag{9}$$

where $S(\cdot)$ denotes the cross product operator.

B. 3-DOF Model for AMVs

The 3-DOF horizontal motion of AMVs is considered, in which the pitch angle θ and the roll angle ϕ are assumed to be small [27]. Neglecting the heavy, roll and pitch elements yields the simplified kinematic equations of AMVs

$$\dot{\eta}' = R(\psi)\nu' \tag{10}$$

where $\eta' = [x, y, \psi]^T$, $\nu' = [u, v, r]^T$, and the rotation matrix $R(\psi) = R_{z,\psi}$.

The 3-DOF nonlinear dynamic motion equation of AMVs is expressed as

$$M\dot{\nu}' + C(\nu')\nu + D(\nu')\nu + g(\eta') = \tau' \tag{11}$$

where $\tau' = [\tau_u, \tau_v, \tau_r]^T$, $M = \mathrm{diag}(m_1, m_2, m_3)$ is the inertia matrix including the added mass and $D(\nu') = \mathrm{diag}(d_1, d_2, d_3)$ denotes the damping matrix, with $m_1 = m - X_{\dot{u}}$, $m_2 = m - Y_{\dot{v}}$, $m_3 = I_z - N_r$, $d_1 = -X_u - X_{u|u|}|u|$, $d_2 = -Y_v - Y_{v|v|}|v|$, and $d_3 = -N_r - N_{r|r|}|r|$. The Coriolis-centripetal matrix is denoted as $C(\nu') = \begin{bmatrix}0 & 0 & -m_2v\\ 0 & 0 & m_1u\\ m_2v & -m_1u & 0\end{bmatrix}$.

Combining (10) and (11), we establish the system dynamics of AMV

$$\dot{x}' = \begin{bmatrix}R(\psi)\nu'\\ M^{-1}(\tau - C(\nu')\nu - D(\nu')\nu' - g(\eta'))\end{bmatrix} = f(x', \tau) \tag{12}$$

in which $f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^n$ with $n = m = 3$; $x' = [\eta', \nu']^T$ and τ' denote the system state and the control input, respectively. For the underactuated AMVs, the number of control inputs is less than the generalized coordinates (i.e., $m < n$). For example, the motion of the ASV possesses 3-DOF (i.e., surge, sway and yaw) while there are only two available control inputs (yaw moment and surge force). The resulting nonintegrable nonholonomic constraint makes the motion control of the underactuated AMVs challenging [28], which is an inspiring research topic within the MPC scheme.

III. MPC for the Motion Planning Of AMVs

A. Introduction

Fig. 5 shows a perception-planning-control hierarchical architecture for AMVs focused on safe and optimal operations. Motion planning of AMVs aims to provide a safe, energy-efficient and timely reference trajectory for the control system of AMVs by determining their distance traveled, position, course, and attitude. The motion planning system directs AMVs to travel in a complex marine environment and arrive at the destination, relying on the information from the human interface, perception layer, vehicle capability, maps, historical data, and environmental conditions.

Many planning algorithms have been developed for AMVs, including optimization-based algorithms (evolutionary algorithm, genetic algorithm), heuristic search algorithms (A^* search algorithm, Dijkstra's algorithm), LOS method, poten-

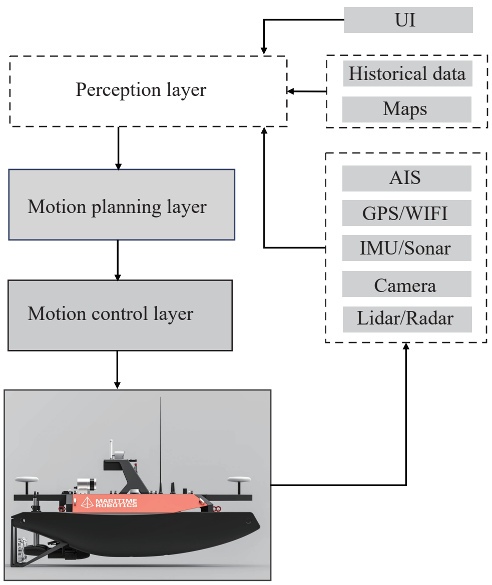

Fig. 5. Architecture for autonomous marine vehicle (AMV) deployment. Solid blocks (motion planning layer and motion control layer) are the scope of this survey. Dash block (perception layer) is not discussed in this survey.

tial field approach, and the rapidly-exploring random trees based method; for a comprehensive overview of works in this topic and further references see the survey papers [8], [20], [29]. These planning algorithms can be employed to address different planning tasks, such as mission planning, route planning, trajectory planning/generation, and path planning [20]. In this survey, we omit the detailed classification of these planning tasks since their boundaries are sometimes blurred. For this reason, we use *motion planning* to represent these planning tasks. To limit the scope of this paper, we focus on the motion planning of AMVs from the perspective of MPC. It is common in MPC-based motion planning to determine the feasible reference trajectory for the control system by minimizing the designed objective function J, subject to the physical constraints. Generally, an model predictive motion planning problem is formulated as

$$\min_{\boldsymbol{x},\boldsymbol{\tau}} J$$

$$\text{s.t. } \dot{x}(s|t) = f(x(s|t), \tau(s|t)), x(0|t) = x(t) \tag{13a}$$

$$g_i(\boldsymbol{x}) \leq 0, i = 1,2,\ldots,n_g \tag{13b}$$

$$h_j(\boldsymbol{x}) = 0, j = 1,2,\ldots,n_h \tag{13c}$$

$$x(s|t) \in \mathcal{X}, \tau(s|t) \in \mathcal{U} \tag{13d}$$

in which $f: \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^n$ denotes the AMV's system dynamics, $\boldsymbol{x} = \{x(s|t)\}$, $s \in [0,T)$ is the predicted state sequence, $x(s|t)$ denotes the predicted system state at future time $t+s$ determined at time t, T is the prediction horizon, $\mathcal{U}$ and $\mathcal{X}$ denote constraint sets of the control input and the state, respectively; $g_i(\boldsymbol{x})$ and $h_j(\boldsymbol{x})$ represent the inequality and equality constraints, respectively. $\tau^*(\cdot)$ is the optimal control input, and $x^*(\cdot)$ is the corresponding optimal system state.

Sophisticated features, including collision avoidance, energy management optimization, and minimum time consumption, can be incorporated into the design of the motion planning system, some of which will be discussed in Sections III-B and III-C.

B. MPC-Based Planning Algorithms for AMVs

The early paper [30] proposes a sampling-based MPC method to simultaneously generate system states and control inputs for nonlinear AUVs in a clustered marine environment, which combines the benefits of sampling-based motion planning with MPC. The kinematic model and motion constraints considered in the motion planning problem ensure the generation of feasible trajectories. Reference [31] describes a novel predictive planning method for AUVs in the presence of forecasting uncertainties and time-varying current disturbances. It is shown that the combined nonlinear MPC and A^* method can generate an energy-efficient path for AUVs under uncertainties. A model predictive motion planner is designed for the underwater vehicle manipulator system; the planner plans the optimal reference trajectory while taking explicitly into account the mechanical limits and control saturation [32].

A unified MPC scheme to handle the tracking control and path planning problem of the AUV is developed in [33]; the authors formulate a new receding horizon optimization problem based on the spline-based planning technique to account for practical AUVs with limited perception capability. In addition, a Lyapunov-based stability constraint is designed and incorporated into the MPC optimization problem to guarantee closed-loop stability. Reference [34] studies the motion planning of underactuated ASVs subject to input constraints, rate and magnitude constraints, and convex/non-convex obstacle constraints. An energy optimal reference trajectory is generated by solving a nonlinear programming (NLP) planning problem for the ASV. A mathematical model-differential flatness is employed to derive a computation-efficient solution to the NLP problem, which achieves a longer prediction horizon while preserving calculation accuracy. The key advantages of MPC-based motion planning algorithms include the capability to explicitly deal with the physical constraints as well as to generate the optimal reference trajectory/waypoint. However, a drawback of these algorithms is that computational cost is high, which has motivated further research on reducing computational burden. Some potentially useful methods such as the embedded MPC [35], triggered MPC [36] and advanced optimization techniques [37] provide some opportunities to deploy the MPC-based planning algorithms on the real-world AMV systems.

C. MPC-Based Collision Avoidance Algorithms for AMVs

This subsection reviews collision avoidance with respect to the design of MPC-based motion planning.

The collision avoidance module plays an essential role in guaranteeing the safety and enhancing autonomy of AMVs; several approaches for AMVs have been reported in the survey papers [16], [19], [22], [26], [38]. When ASVs operate in inland waterways and urban canals, they must obey policy regulations. Thus, the policy-aware MPC-based motion planning becomes significant for the safety-critical AMVs. The COLREGs rules describe several collision scenarios such as head-on, overtaking, crossing from right and crossing from left as shown in Fig. 6. In [39], the mathematical interpretations of COLREGs rules are considered in the objective function design of the MPC-based motion planning problem. Recursively solving the MPC problem yields the protocol-aware collision-free system trajectory for ships subject to wind and ocean current. Further experimental results of MPC-based collision avoidance algorithm implementation on AMVs are presented in [40], [41]. A recent paper [42] proposes a regulation-aware motion planning method for the ASVs in unstructured urban canals; the method builds on local model predictive contouring control to generate a collision-free and regulation-aware reference trajectory for ASVs in the presence of static and dynamic obstacles. In order to enable the ASVs to be aware of the interaction regulations, a cost function encouraging compliance with COLREGs rules is designed for the MPC problem. It is worth mentioning that the above method cannot guarantee collision avoidance. One may introduce the regulation policy-based constraint into the MPC optimization problem to ensure collision avoidance for AMVs under different working conditions.

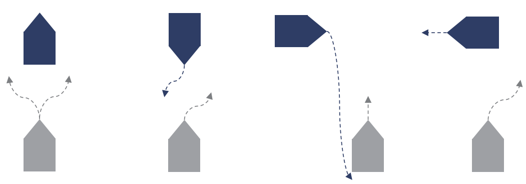

Fig. 6. COLREGs maneuvers for different situations. The scenarios are illustrated from the gray vessel's viewpoint: (a) Overtaking; (b) Head-on; (c) Crossing from port; (d) Crossing from starboard.

A different approach in [43] that combines the Hamilton-Jacobi differential game method with MPC is introduced to enable safety-guaranteed trajectory planning for AUVs under the progressive waves. A position-dependent and time-varying function simulates wave disturbances; a Hamilton-Jacobi method computes the value function and level set. The set is then substituted into the MPC problem to plan a safe reference trajectory for AUVs. A robust MPC-based motion planning method is proposed for the URV operating in the constrained workspace [44]. Different constraints such as control inputs, constrained workspace, and obstacles are considered within the MPC framework. Experiments validation carried out on a small URV demonstrates the effectiveness of the robust model predictive motion planning scheme. A key challenge in these strategies appears to be their application to AMVs in complex, dynamic and confined environments. In [45], a finite control set based MPC is designed for motion planning of ASVs under uncertainties. The cost function for the MPC problem includes four sub-functions, which correspond to stability, reachability, rapidity, and safety. The control set and the delay compensation are used to balance the trade-off between planning and calculation accuracy.

In [46], a distributed MPC (DMPC) approach is proposed for trajectory planning and coordination of multiple AMVs. Each AMV solves a local DMPC optimization problem and communicates with the neighbors to reach a consensus on collision-free trajectories. The DMPC problems are calculated in parallel using a modified alternating direction method of multiplier (ADMM) scheme. The collision avoidance approach in [47] that combines MPC with the Q-learning beetle swarm antenna search algorithm is investigated to solve the problem of multi-ship encountering. Reference [48] develops a disturbance observer-based DMPC algorithm for motion planning with the guarantee of the connectivity maintenance and collision avoidance of multiple ASVs subject to varying environmental disturbances. Feedback control can mitigate the effect of external disturbances by using the estimates of the disturbance observer. The idea in [43] is extended in [49], where collision-free trajectory planning of multiple AUVs is considered.

Finally, an emergency scenario is worth mentioning where the AMVs cannot operate normally. In [50], an MPC method is designed for trajectory generation and emergency management of ASVs; the planning and risk costs in the objective function correspond to different aspects of normal planning and different emergency cases. The resultant risk-based motion planning method may serve as a foundation for human operators and a safe motion planner for ASVs.

IV. MPC FOR THE MOTION CONTROL OF AMVS

At large, motion control of AMVs is the control input of determining the needed forces and moments for the AMVs with the aim of achieving a specific control objective. Different motion control problems of AMVs have been widely discussed in the literature, such as dynamic positioning control, trajectory tracking control, path following control, and cooperative control [2], [7], [8]. This section focuses on MPC for the motion control of AMVs. The reference for the MPC block varies with different control objectives, as shown in Fig. 7. Note that different observers, such as the disturbance observer and extended state observer (ESO) can be developed to estimate the system states of AMVs affected by wind, wave and ocean current forces. To limit the scope of this review, we focus on the motion control of AMVs in this section.

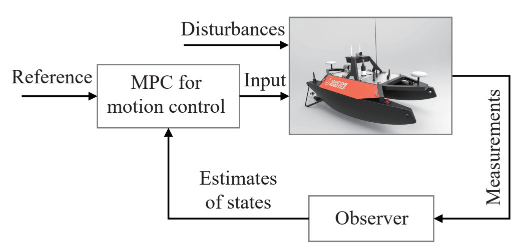

Fig. 7. Illustration of MPC for the motion control of AMVs.

A. MPC for Dynamic Positioning of AMVs

Dynamic position (DP), also known as station keeping, is one of the representative control tasks for AMVs under complex marine environments, which requires the AMV to maintain a pre-specified position and orientation $\eta_d = [x_d, y_d, \psi_d]^T$ exclusively by means of thruster force, see [15] and the references therein. MPC-based DP controller can achieve good control performance and reduce energy consumption in situations with limited thrust. The optimal DP control inputs $\boldsymbol{\tau}'^*(t) = \{\tau'^*(s|t)\}$, $s \in [0,T)$ are determined by solving a finite horizon MPC optimization problem at time t as follows:

$$\min_{\tau'(t)} J$$

$$\text{s.t. } \dot{x}'(s|t) = f(x'(s|t), \tau'(s|t)) \tag{14a}$$

$$x'(0|t) = x'(t) \tag{14b}$$

$$\tau'(s|t) \in \mathcal{U} \tag{14c}$$

$$x'(s|t) \in \mathcal{X} \tag{14d}$$

in which $s \in [0,T)$, T is the prediction horizon, $\mathcal{X}$ and $\mathcal{U}$ denote constraint sets of the system state and the control input, respectively; $J = \int_0^T (\|\eta'(s|t) - \eta_d\|_Q^2 + \|\tau'(s|t)\|_R^2) ds + \|\eta'(T|t) - \eta_d\|_P^2$, with the positive definite matrices Q, R and P. The optimal control input $\tau'^*(s|t)$, $s \in [0,\delta]$ is applied to the AMV system iteratively, with δ being the sampling period.

The early papers [51] and [52] dealing with the DP control problem of constrained AMVs via the MPC approach has a substantial impact. However, only the 1-DOF heading problem is addressed for the marine surface vessels without considering state constraints. A novel disturbance compensation-based MPC algorithm is developed to address the heading control problem of a linear constrained vessel subject to time-varying environmental disturbances; disturbance compensation control Δu is calculated not only to ensure recursive feasibility but also to retain the control performance achieved by the ship without disturbances [53]. The MPC-based DP algorithm in [54] replaces originally separate solutions of position control and thrust allocation (TA) by solving a single MPC problem that combines DP and TA, resulting in improved control performance and reduction of energy consumption. Reference [55] proposes an MPC approach, which uses a linear wave solver to estimate the ocean forces acting on underwater robots to mitigate disturbances from an ocean wave field.

Furthermore, [56] presents the experimental validation of the MPC architecture for the station keeping problem, which incorporates the estimation model of hydrodynamic forces induced by regular and irregular waves into the architecture. Understandably, it is essential to ensure closed-loop stability in practical applications; establishing the stability of general linear or nonlinear systems with constraints by adding the terminal constraint and cost has been well-addressed [9]. To guarantee closed-loop stability and circumvent the complex terminal set design for the nonlinear AMVs, the authors in [57] propose a Lyapunov-based stability constraint for the MPC-based DP optimization problem.

However, most MPC algorithms mentioned above cannot be applied directly to the DP problem of the underactuated AMVs with nonholonomic constraints. In [58], a novel MPC algorithm is proposed for the constrained underactuated AUVs based on homogeneous system dynamics and a time-varying feedback control law [59]. More recently, robust dynamic positioning problems using tube-based MPC have been studied for the ASV in the presence of environmental disturbances [60], [61]. The same problem is addressed in a different way [62]. A disturbance observer is developed to approximate environmental uncertainties; the control input generated by solving the NMPC optimization problem can reject disturbances by incorporating disturbance estimation into the prediction model under the NMPC scheme.

B. MPC for Path Following of AMVs

Path following control refers to the case where the AMV follows a feasible time-invariant path with desired speed and orientation. Note that no temporal restrictions are imposed on the predefined path. Much attention has been paid to the path following problem of nonlinear continuous-time AMVs represented by:

$$\dot{x} = f(x, \tau)$$

where the system states and control inputs of AMVs are required to satisfy $x \in \mathcal{X}$ and $\tau \in \mathcal{U}$. Note that the desired path $x(\gamma)$ is usually parameterized by a variable γ, $\gamma \in \mathbb{R}$. The path following problem is addressed by transforming the original control problem into the regulation problem based on error dynamics. The error dynamics take the following form:

$$\dot{x}_e = f(x_e, \tau)$$

where the error state x_e includes the heading error and cross-track error. The Serret-Frenet frame [27] is usually used to derive the error dynamics in path following problem. The control input is generated by solving the following MPC optimization problem at time t:

$$\min_{\tau(t)} J$$

$$\text{s.t. } \dot{x}_e(s|t) = f(x_e(s|t), \tau(s|t)) \tag{15a}$$

$$x_e(0|t) = x_e(t) \tag{15b}$$

$$\tau(s|t) \in \mathcal{U} \tag{15c}$$

$$x(s|t) \in \mathcal{X} \tag{15d}$$

in which $s \in [0,T)$, T is the prediction horizon, $x_e(s|t)$ represents the predicted error state at future time $t+s$ determined at time t; $J = \int_0^T (\|x_e(s|t)\|_Q^2 + \|\tau(s|t)\|_R^2) ds + \|x_e(T|t)\|_P^2$, with the positive definite matrices Q, R and P.

A pioneering work appears in [63]; an MPC approach employing the error dynamics is proposed to solve the path following problem of ASVs subject to roll constraints and wave disturbances. Reference [64] provides an experimental implementation of the MPC-based path following algorithm on the constrained ASVs. A novel solution to this problem is described in [65] which considers the path following of underactuated ASVs with input constraints. Here, the error dynamics are obtained with respect to the LOS guidance reference. Then, an MPC method generates the feasible path for the ASV to follow based on good helmsman behavior. Moreover, embedding the LOS parameter as an additional decision variable of the MPC optimization problem provides an extra DOF in improving control performance. In [66] and [67], the authors provide an output nonlinear MPC algorithm for solving the path following control problem. As a special case of the path following task, the straight line following problem of the constrained underactuated AMV with disturbances is addressed by deploying a real-time MPC algorithm in [68].

The simulation results and on-sea experiments illustrate good performance under the proposed algorithm.

The speed assignment is considered in the path following problem in [69], where an explicit parameterization of the zero-path-error manifold is constructed for the MPC design. A novel multi-objective MPC method is designed for the AUVs to balance the vehicle's speed assignment and the path convergence rate. The lexicographic ordering and weighted sum methods are studied to solve the multi-objective MPC optimal problem. The work reported in [70] proposes a robust control method by combining the disturbance observer, adaptive Kalman filter, and robust MPC to solve the path following and rudder stabilization problems of the underactuated ASV subject to roll constraints and environmental uncertainties. To reduce computational requirements, the authors in [71] leverage the neurodynamic optimization technique to accelerate the computation speed of the multi-objective MPC problem.

A recent paper [62] investigates the energy-optimal path following control problem of the AUVs with limited onboard energy resources and ocean currents. An energy-optimal LOS-MPC method is developed by considering the surge speed optimization in the LOS guidance path following problem. The authors further extend the MPC algorithm for the three-dimensional energy-optimal path following problem of AUVs subject to ocean currents.

In addition, collision avoidance is discussed in the path following task of the ASV in confined environments. This problem is addressed by adding the dual collision avoidance constraint into the MPC-based path following optimization problem [72], [73]. The path following control problem becomes challenging if AMVs' dynamics vary during operation due to speed changes, load changing, parametric uncertainties, and external disturbances. This is the case investigated in [74]. The authors propose an adaptive MPC method that uses the least squares support vector machine to address the path following problem of the underactuated ASVs with varying system parameters. The proposed controller consists of the MPC design and the online identification of varying parameters. On the other hand, MPC algorithms have been exploited for path following control of the fully-actuated AMVs [63], [69] and underactuated AMVs [65], [68], [70], [75].

C. MPC for Trajectory Tracking of AMVs

The trajectory tracking task is concerned with the control design such that the AMV is driven to track a temporal and spatial trajectory. The reference trajectory is usually assumed to be generated by a virtual AMV, i.e., the time-varying reference trajectory x_r satisfies the system dynamics in (12)

$$\dot{x}_r = f(x_r, \tau_r)$$

where τ_r is the reference control input concerning the reference trajectory. Define the tracking error state $x_e = x - x_r$, after which one obtains the tracking error dynamics

$$\dot{x}_e = f(x_e, \tau).$$

Based on the error dynamics the tracking problem for the original AMV system in (12) is converted into a stabilization problem. The tracking MPC problem is similar to the path following problem as in (15). Iteratively solving the constrained optimization problem yields the optimal control input sequence, and the first element of the calculated sequence is applied to the AMV. The constraints on states and inputs, highly nonlinear dynamics and unpredictable sea environment lead to technical difficulties in developing the trajectory tracking controller for AMVs. In [76], a neurodynamic-based MPC approach is developed for the trajectory tracking control of underactuated ships with external disturbances, where a two-layer recurrent neural network is adopted to calculate the minimax optimization problem iteratively. This approach is extended to address a wide range of underactuated systems with guaranteed closed-stability in terms of kinematics and kinetics [77]. The MPC-based three-dimensional trajectory tracking strategies for constrained AUVs are reported in [78]−[80].

Intuitively, the excessive computational requirements of nonlinear MPC methods impede their implementation for real-world AMV applications. To alleviate computational complexity, several solutions have been developed, which can be broadly categorized into: i) simplifying the optimization problem [81], ii) the fast optimization algorithm [82], and iii) distributed and parallel computation [83]. A real-time nonlinear MPC method for the tracking problem of ASVs subject to the influence of unknown ocean currents is presented in [81]; an augmented model is constructed by incorporating the actuator physical limitations into the prediction model itself based on smooth saturation functions. The method simplifies the MPC design process because it is unnecessary to consider the input constraints in the optimization problem. In [82], a modified Ohtsuka's continuation/generalized minimal residual algorithm has been developed to shorten the computation time of the nonlinear MPC optimization problem for AUVs. The Pontryagin's minimum principle is exploited to solve the Karush-Kuhn-Tucker conditions. The authors in [83] develop a distributed computation framework for the nonlinear MPC-based trajectory tracking control problem. The method appropriately decomposes the original tracking MPC problem into three smaller subproblems and then solves them in a distributed fashion, significantly reducing computational complexity. Moreover, the AUV's closed-loop stability is guaranteed by adding a stability contraction constraint [84] into the MPC tracking optimization problem. There remain interesting and challenging problems in the real-time implementation of nonlinear MPC algorithms.

Results from the robust MPC [85] are usually employed to enhance the robustness of AMVs against parametric uncertainties and environmental disturbances. The robust MPC method is designed for the tracking problem of the AMV in the presence of external disturbances [44], [86]. The Kalman filter or other types of observers are employed for AMVs to compensate for external disturbances, measurement noises, and modeling uncertainties; see [87]−[92]. The same problem is solved differently in [93]. In order to handle external disturbances and model mismatch, the method uses reinforcement learning and system identification techniques to update the prediction model for the nonlinear MPC online, resulting in improved closed-loop control performance. Payload variation

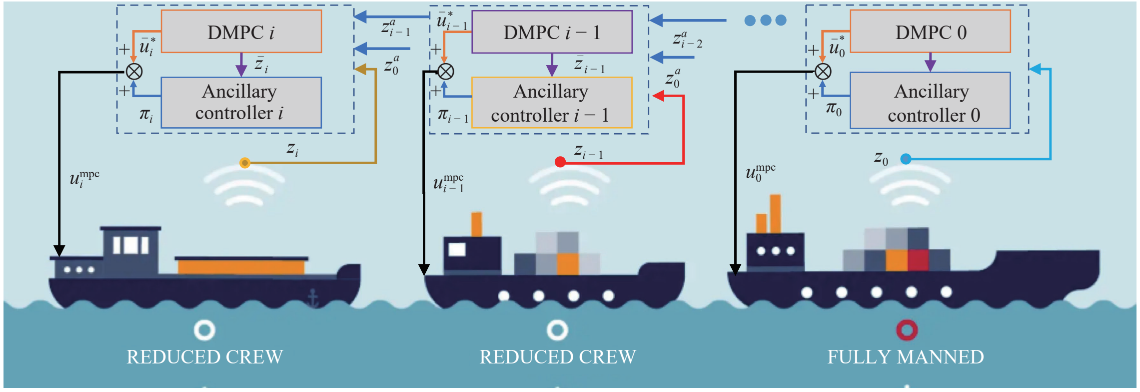

Fig. 8. Illustration of the DMPC for cooperative ASVs [106].

may lead to significant changes in the AMV's dynamics, thereby degrading control performance. A nonlinear adaptive MPC method is applied for the tracking control of ASVs with largely varying payload [94]. The thruster fault of AMVs is considered in [95]. The tracking method combining the quantum-behaved particle swarm optimization with MPC reallocates thruster forces for AMVs with thruster failure.

Regarding practical applications, the challenges such as accurate system dynamics, algorithm deployment, and code debugging make theoretical results hard to verify on the testbed AMV. The researchers generally verify the theoretical results with simulation studies, and few studies have the AMV experimental validation of the MPC algorithm. Recently, some experimental tests are conducted to illustrate the tracking performance of the AMVs under the MPC algorithms [93], [96]–[100].

D. MPC for the Cooperative AMVs

Compared with the single AMV, cooperative AMVs can perform more complicated marine tasks. One fundamental control task of the cooperative AMVs is formation tracking control, which requires multiple AMVs to maintain a prespecified formation and track the reference trajectory simultaneously. Some appealing control methods have been developed to tackle this problem, e.g., the virtual structure control method [101], the leader-follower method [102] and dynamic output feedback control method [103]. In particular, some practical network-induced issues such as packet dropout, delays and disordering information transmission among the cooperative AMVs are considered in [103] and [104]. Unfortunately, these methods cannot optimize control performance or handle the cooperative AUVs with constraints [105]. Alternatively, the DMPC method is an ingenious solution to this problem. Loosely speaking, a classification of existing DMPC algorithms can be made according to the coupling source, namely DMPC with coupled cost and coupled constraints. The cooperation component is introduced in an optimization problem via the coupled cost function $V_i(x_i,x_j,u_i)$, which is optimized by each AMV i

$$V_i(x_i,x_j,u_i)=\sum_{j\in\mathcal{N}_i}\ell_i(x_i,x_j,u_i)+V_i^f(x_i) \tag{16}$$

where x_j denotes the neighboring state information of AMV j, $j\in\mathcal{N}_i$, $\mathcal{N}_i$ is the neighbor set of AMV i, u_i denotes the control input, $\ell_i(x_i,x_j,u_i)$ and $V_i^f(x_i)$ are the coupled stage cost function and the local terminal cost function, respectively.

Regarding the system constraints, most of the aforementioned DMPC algorithms may not be feasible for the AMVs with global coupled constraints as in (17c). However, this type of constraint plays an essential role in many practical applications, for instance, controlling a group of M AMVs while avoiding collisions and preserving connectivity. It is noted that the main challenge lies in guaranteeing the satisfaction of coupled constraints in a distributed manner as follows:

$$x_i\in\mathcal{X}_i,\ i=1,2,\ldots,M \tag{17a}$$

$$\tau_i\in\mathcal{U}_i,\ i=1,2,\ldots,M \tag{17b}$$

$$\sum_{i=1}^{M}(\Psi_i^x x_i+\Psi_i^u\tau_i)\leq\mathbf{1} \tag{17c}$$

where x_i and τ_i denote the system state and the control input, respectively. $\mathcal{X}_i\subset\mathbb{R}^{n_i}$ and $\mathcal{U}_i\subset\mathbb{R}^{m_i}$ are the local constraint sets of state and control input of AMV i, $i=1,2,\ldots,M$, respectively. $\Psi_i^x\in\mathbb{R}^{p\times n_i}$ and $\Psi_i^u\in\mathbb{R}^{p\times m_i}$ are matrices used to define the globally coupled constraints, with $\mathbf{1}$ being the all-one vector of proper dimensions. In distributed coordination, each AMV calculates its control inputs $u_i^{\rm mpc}$ by solving the local DMPC problem based on the local measurement and the neighbors' information, as indicated in Fig. 8. Note that the control input $u_i^{\rm mpc}$ for ASV i consists of two control terms: 1) the nominal control input $\bar{u}_i^*$ generated by solving the constrained DMPC optimization problem, which drives the nominal error state to zero, and 2) the auxiliary control law π_i that keeps the actual error state staying in a specified neighborhood of the nominal error state.

In [107], a distributed path following controller is proposed for the cooperative vessels, in which the ADMM is adopted to accelerate the convergence rate of solving the DMPC problem. In addition, a coupled collision avoidance constraint as in (17) is considered in the DMPC problem. This method is further extended in [108] to deal with environmental uncertainties. Especially, the authors apply DMPC algorithms for multiple ASVs to enhance the efficiency of urban waterway transport in [106], [109]–[111]. Reference [112] presents a new DMPC approach to address the formation tracking problem of cooperative underactuated AUVs; the terminal set and the terminal control law are designed for the DMPC problem. The

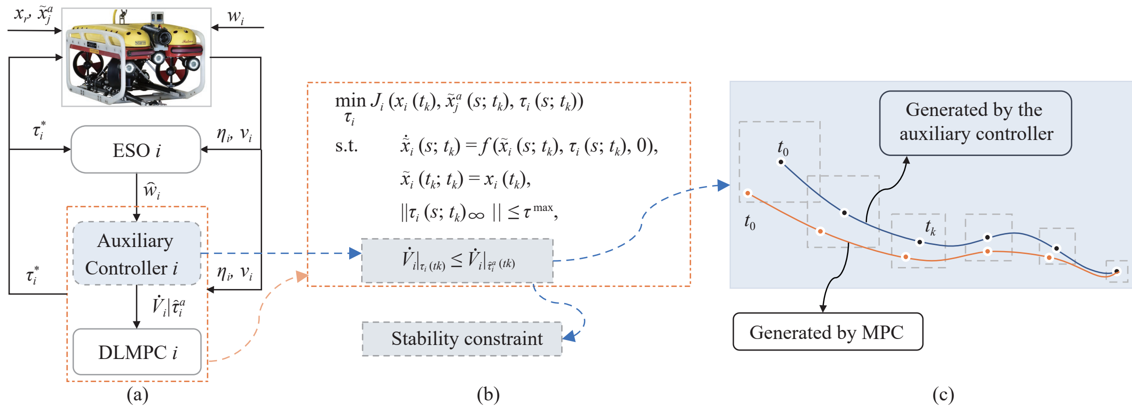

Fig. 9. Illustration of the Lyapunov-based DMPC (DLMPC) for cooperative AUVs [114]: (a) The DLMPC control scheme; (b) The DLMPC optimization problem; (c) The contraction property. An additional state constraint (i.e., the stability constraint) constructed via an auxiliary controller is incorporated into the DMPC problem, which renders the closed-loop cooperative AUV systems stable. A similar idea of imposing a contractive property on the closed-loop system to a nonlinear MPC framework is reported in [115]. Note that η_i, v_i, τ_i, $\hat{\tau}_i^a$ and w_i denote the position, the velocity, the control input, the auxiliary control law and the ocean current disturbance, respectively. $\dot{V}_i|_{\tau_i}$ denotes the derivative of Lyapunov function under the control law τ_i.

conditions that ensure the closed-loop stability and the recursive feasibility of the DMPC-based formation tracking algorithm are provided. A similar formation control problem of multiple cooperative ASVs in the presence of obstacles is also studied in [113].

However, the stability analysis by local linearization is practically hard for AUVs since they have complex nonlinear system dynamics. This poses great challenges in the design of the terminal set. To overcome this difficulty, the authors in [84], [116] proposed the Lyapunov-based MPC method, which avoids the local linearization and adds a stability constraint generated by a Lyapunov-based controller to the original MPC scheme, thereby guaranteeing closed-loop stability and improving the control performance. A DLMPC-based formation tracking method is designed for cooperative AUVs subject to environmental disturbances; collision avoidance is also guaranteed during the operational period relying on the proposed collision avoidance cost function [114]. The DLMPC method inherits the robustness and stability properties of the ESO-based auxiliary controller and invokes online optimization to further enhance the control performance of cooperative AUVs. The cooperative AUVs' closed-loop stability is guaranteed by the stability constraint as illustrated in Fig. 9. It can also be shown [117] that the formation tracking and collision avoidance of underactuated ASVs with dynamical uncertainties are achieved under the ESO-based DMPC method.

Regarding the limited communication resources of the AUVs, an event-triggered DMPC method is designed to alleviate the communication burden [118]. Furthermore, the authors in [119] propose a novel real-time DMPC approach for cooperative AUVs with limited communication data rates. The optimal quantization design guarantees that the sub-optimality is achieved, in which a warm-starting strategy is employed to solve the DMPC optimization problem.

In addition to the literature on safe DMPC for cooperative AMVs under uncertainties, there are limited results on this topic. The collision avoidance safety of cooperative AUVs in [114] is established by adding a coupled collision avoidance cost term into the overall objective function. On the other hand, the inter-vehicle safety of the AMVs is guaranteed by imposing a coupled collision avoidance constraint in the DMPC optimization problem [46], [106], [109], [117]. Recently, an alternative method is developed in [120]; the barrier-certified DMPC method enables the underactuated ASVs to avoid static and dynamic obstacles. Experimental evaluation of DMPC for cooperative ASVs is provided in [121]. Field experiments of cooperative AMVs under the DMPC algorithm still deserve further study.

E. Other Topics

Some other research topics in MPC for the control of AMVs have received less attention but have considerable potential. We briefly introduce these topics in this subsection.

Visual Servoing: Visual servoing usually employs image data as feedback to steer the autonomous intelligent system to a predefined visual target position [122], [123]. A visual servo MPC scheme is developed for the URV in [124], in which the field of view constraint used as the visual constraint is added to the MPC problem. The image processing and the optimization algorithm are running at triggering instants. References [125] and [126] propose a hierarchical control approach for the AUVs and underwater vehicle manipulator systems, which combines the MPC with the visual servoing control. The cost function is designed depending on the visual state errors, and the constraints on the features' visibility in the image plane are incorporated into the MPC optimization problem.

Energy Optimization: Another important consideration in the motion control of AMVs is optimizing energy consumption under different operational conditions. This is because energy-efficient management can significantly improve the endurance of AMVs with limited onboard energy resources, thereby reducing the operational costs and improving application range [62], [127], [128]. An economic MPC approach is proposed in [128] for the waypoint tracking of AUVs while reducing energy consumption. The proposed approach optimizes the stage cost by including the energy consumption in the prediction horizon and the terminal cost by estimating the energy required to reach the desired waypoint. In [62], an

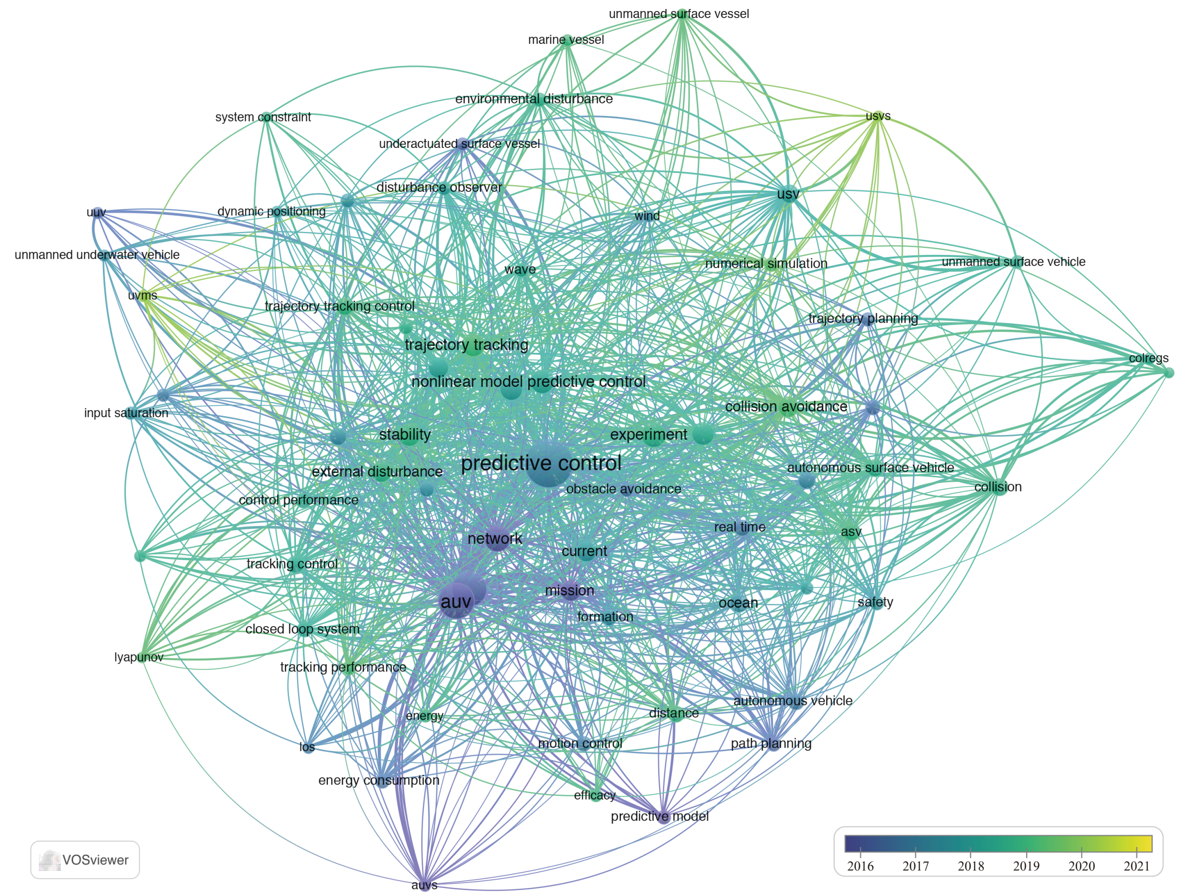

Fig. 10. Research trends on motion planning and control of AMVs, which is generated by VOSviewer from 488 papers. Source: WOS.

energy-optimal LOS-MPC method is developed to solve the path following control problem of AUVs under uncertainties. The proposed method optimizes energy consumption in the LOS guidance-based path following scheme. A DMPC-based bi-level distributed dynamic method is proposed to optimize the energy consumption of ship fleets [129]. Another area is concerned with the deployment of MPC methods for the energy production optimization of the ocean wave energy converter [130].

Autonomous Docking Control: Generally, the autonomous docking mission can be split into two phases: the long-range, in which the AMVs are steered to an area near the docking target; and the short-range, during which the AMVs are precisely controlled to the docking target with satisfaction of the safety constraint, localization requirement, and other types of constraints [131]. On the other hand, the autonomous docking mission involves the motion planning and motion control operations; solving the former problem yields the reference trajectory for the latter problem. The application of MPC for autonomous docking of AMVs has received some attention, e.g., [132]–[134]. MPC in such AMVs' docking studies remains to be further studied.

V. Future Directions

As shown in Fig. 10 , the word cloud generated by the VOSviewer [135] shows the research of MPC-based motion planning and control for AMVs, in which the color of the clusters indicates the research trends in this field. Fig. 10 illustrates the hot research topics, such as cooperative ASVs, collision avoidance, formation, uncertainties, and energy efficiency. Note that the word cloud is based on the search results in WOS with the title keywords such as "model predictive control", "motion planning", "motion control", "collision avoidance", "receding horizon control", "predictive planning", "autonomous surface vehicle", "autonomous underwater vehicle", "marine robot" and "autonomous marine vehicles".

MPC algorithms have been successfully applied to AMVs for generating a safe reference trajectory and optimal control inputs. They have the advantages of explicitly dealing with constraints and optimizing planning and control performance online. Although massive research efforts have been devoted to this field, it is still desirable for practical AMV applications to develop planning and control algorithms that are effective, reliable, intelligent, robust and energy-efficient. Here we highlight some potential directions and opportunities for future research.

A. Data-Driven Predictive Planning and Control for AMVs

The prediction model, such as the state-space model or input-output model for the AMVs, is an essential ingredient of conventional MPC design, based on which AMV's behavior is predicted and optimized over a finite-time horizon. That is, the system model's accuracy greatly influences planning and control performance. In practice, the AMV system model is rarely known a priori and has to be identified from the offline collected input and output data [136]. MPC then leads to a two-stage procedure consisting of system model identification and controller design. However, an accurate system model for AMVs is hard to obtain due to complex hydrodynamic forces, uncertainties and nonlinear dynamics. In this case, data-driven approaches are investigated with the aim of constructing the controlled system directly from data without the intermediate system identification step [137], [138]. Recently, several data-driven predictive control approaches that combine the data-driven idea with MPC are proposed in [139]–[141]. These approaches leverage the previously measured input/output data to predict the unknown system's behavior and calculate the optimal control inputs to steer the system along the desired trajectory. It should be noted that applying these data-driven predictive control approaches for the motion planning and control problems of the constrained AMV systems deserves further investigation.

B. Real-Time MPC for Planning and Control of AMVs

Although MPC algorithms have been widely investigated to address motion planning and control problems of constrained AMVs, the intractable computational complexity inhibits their application for real-time AMVs with limited onboard computational resources. There have been various solutions to this challenging problem, ranging from explicit MPC [142], [143] to DMPC [12], [144], [145]. Other noteworthy approaches include distributed optimization [37], accelerated optimization algorithm (e.g., Ohtsuka's continuation/generalized minimal residual algorithm [82]) and warm-starting techniques [146], [147]. The real-time implementation of the motion planning and control algorithms for nonlinear AMVs is still challenging, and further research along this line is needed.

C. MPC for Cooperative AMVs

In order to perform more complex missions, improve application range, and reduce operational costs, cooperative AMV systems become necessary. However, most existing AMV research results focus on cooperative motion planning and control with applications to: 1) cooperation among AUVs, such as formation tracking of AUVs [114], formation stabilization [58]; 2) cooperation among ASVs, including platooning control [106], waterborne transport [107], [148]. We call these applications homogeneous AMVs (or horizontal AMV systems). In contrast, the heterogeneous AMVs (vertical AMV systems), including the combined ASV-AUV systems [149], cooperative ASV-unmanned aerial vehicle (UAV) systems, and cooperative AUV-ASV-UAV systems, do not appear to have received much attention. These vertical applications open up great possibilities for future offshore exploration and detection, which, however, require more advanced and intelligent planning and control algorithms. DMPC-based motion planning and control algorithms provide opportunities to enable these cooperative AMV systems to be smarter, safer and more efficient.

D. MPC as a Service for AMVs

The emerging cloud-edge computing and communication technologies are reshaping the development of autonomous intelligent systems, including automated vehicles, AMVs, UAVs, and industrial robots. The concept of control as a service (CaaS) is first present in [150], which studies a cloud-based control scheme and deploys all control functions on the cloud for the automated vehicle. Subsequently, an MPC as a service (MPCaaS) framework is developed for cyber-physical systems [151]. The MPCaaS framework combines cloud computing technology and elliptic cryptography-based encryption communication. The existing planning and control algorithms for AMVs are usually embedded inside the controlled systems, which may have a high requirement on the computational resources. The MPCaaS scheme can perform computations remotely, thereby greatly alleviating the onboard computational burden. For the deployment of real-world AMVs, the computationally demanding motion planning mission can be deployed on the cloud; the motion controller can be implemented on the vehicle. We anticipate further study of MPCaaS for motion planning and control of AMVs.

E. AMVs With Guaranteed Resilience and Security

Typically, the information is exchanged in a distributed fashion for cooperative AMVs without a central collection and process. Potential malicious intrusions and adversarial attacks may exist in the communication networks, leading to network vulnerability or damage. Resilient and secure control approach becomes critical when some AMVs under malicious attacks do not obey the predefined communication rule and try to mislead the other AMVs. The objective is to achieve cooperation of normal AMVs, depending on reliable information of their neighbors. There has been a growing interest in studying systems' resilience and security under cyber-attacks in the control community. Several resilient and secure control methods have been developed in [152]–[156], but the problem of MPC for AMVs with guaranteed resilience and security still exists. Conventional cooperative protocols are not applicable for the security-critical AMVs with constraints. Some effective attack detection algorithms need to be developed within the MPC scheme to address AMVs' motion planning and control problems with guaranteed resilience and security.

F. Long-Term Autonomy of AMVs

When we think about long-term autonomy here, the questions are 1) whether the AMVs can perform entire tasks with guaranteed optimality and safety under complex marine environments without human intervention; 2) whether AMVs can optimize energy consumption to improve application range and endurance. In terms of the long-term autonomy, multiple subtasks may be required to be accomplished during the AMV operations under complex marine environment [157]–[159]. Switched and adaptive learning MPC may be a promising solution to this problem [160], [161]. In addition to multiple missions, environmental disturbances and uncertainties may cause adverse effects on the implementation of long-term autonomy for AMVs. Moreover, some energy-optimal planning and control strategies have been proposed for AMVs in [128], [62]. This problem is still open, and further research in this area is anticipated.

G. Experimental Validation of AMVs

As highlighted in [8], thus far most of the research works on the planning and control of the AMVs are still verified via simulation studies. Even though some interesting experiment results have been reported in [40], [41], [93], [96]−[100], [121], more advanced and effective MPC-based motion planning and control strategies are desired for the real-world AMVs. In particular, less attention has been paid to the experimental validation for the cooperative AMVs. Emerging technologies such as cooperative DMPC [162]−[164], distributed optimization [165] and advanced communication algorithms offer opportunities to deploy motion planning and control algorithms on real cooperative AMV experimental platforms.

VI. Conclusion

This paper presented a comprehensive overview of recent advances in the motion planning and control studies of AMVs from the perspective of MPC. System modeling of conventional AMVs was firstly provided. Furthermore, state of the art MPC-based motion planning algorithms were developed for AMVs (including the AUVs, ASVs, ROVs, and URVs), and were summarized and discussed. Some of the challenges in motion planning arose from an uncertain marine environment, the expensive computational costs, and required cooperation between multiple AMVs, which have motivated further research on effective and reliable motion planning algorithms for AMVs. In what follows, the MPC-based motion control algorithms for AMVs were systematically summarized by four aspects of dynamic positioning control, path following control, trajectory tracking control and cooperative control. Although a lot of research results were available in the literature, the smarter and safer MPC-enabled motion planning and control algorithms for the AMV applications remained open and challenging. Finally, some promising future directions in this research area have been elaborated, such as data-driven MPC planning and control for AMVs, MPC for cooperative AMVs, MPCaaS for AMVs, safe MPC for AMVs and experimental validation.

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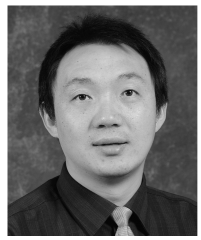

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