Data-Driven Control in Marine Systems

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Abstract

With the advent of cheap smart sensors installed on board marine vehicles and the increasing computational power of small embedded processors there is tremendous potential for the implementation of new strategies to control marine systems on the basis of input-output plant data. The emerging field of smart sensors affords a unique opportunity to have access to on-line measurement of dynamical systems' variables seamlessly, at a low price. By applying a data-driven control algorithm to a marine vehicle, the paper introduces a new perspective on how data can be used in the control loop in marine systems. Classical control methodologies start by developing a model of the plant to be controlled, after which a number of control design techniques can be used. Recent advances in so-called model-free data-driven control methodologies, in particular unfalsified control, hold promise to merge the identification and control phases. Unfalsified control techniques build on the construction of a bank of controllers for a given plant, in which there exists at least one controller that meets the desired performance specification and a falsification unit. The latter is implemented using a cost function that directly evaluates the performance of

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the controllers (in and out of the feedback loop) using measured input and output data. At each sampling time, the performance of the controllers is assessed and the controllers that do not meet the pre-defined performance specification criteria will be falsified and removed from the bank of the controllers, after which an active controller will be selected among the unfalsified ones. In this paper, by presenting the results of the application of unfalsified control to the problem of Dynamic Positioning (DP) of marine vessels subjected to environmental forces, we aim to attract the attention of researchers in the field of marine control to the new perspective of using data to directly control marine system.

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1. Introduction

Seamless access to the states of a marine vehicle, thanks to the availability of cheap smart sensors installed on board, affords unique opportunities to devise new strategies for the control of dynamical systems on the basis of plant input-output data only. In general, controlling a dynamical system using classical control theory starts with the derivation of the general model equations that govern its behaviour from first physics principles, followed by model parameter identification based on collected input/outputa data. Many different control techniques have been developed to try and merge the identification and control phases in a single step. To this end, adaptive control theory has been able to deliver promising performance in the control of uncertain systems by adapting the plant model/controller according to the collected input/output data. Among different adaptation algorithms, adaptive switching control (ASC), as an alternative to conventional continuous adaptation, has proven to have a faster rate of convergence [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]. In ASC, the adaptation algorithm using the measured input/output data selects a controller from a family of candidate controllers, and inserts it into the feedback loop. The measured input/output data are used to evaluate the performance of the controller in the loop, and if necessary replace the active controller with another candidate controller from the bank of controllers. While most ASC methodologies use a dynamic model of the plant in their adaptation and controller selection phases, the control technique exploited in this paper, entitled unfalsified control, relies solely on the measured input/output data for evaluating the performance of the controllers, even for the candidate controllers that have not been activated in the feedback loop. See [9, 10, 11, 12] and the references therein for a fast paced introduction to this control technique and a number of applications.

The main contribution of the current paper is the application of a data-driven model-free unfalsified control methodology to the dynamic positioning and control of marine systems subject to environmental forces, such as wind and waves. The efficacy and the potential of this technique for real-life applications are assessed in a simulation environment. From a theoretical and practical standpoint, the work is ongoing, and important issues remain as work-in-progress. However, we believe that with the increase in computational power and the seamless access to the states of a marine vehicle, there is tremendous potential for the development of new effective strategies to control marine systems. Accordingly, in this article we aim to direct the attention of researchers in the field of marine control to the potential benefits of model-free data driven control. We show how, with some minor modifications, unfalsified control theory, as a true performance based design approach, can be applied in the field of marine control systems.

The structure of the paper is as follows: Section 2 presents a brief introduction to dynamic position; Section 3 gives an introduction to unfalsified control theory; Section 4 describes the simulation model that is used for numerical simulation of the proposed DP controller; Section 5 presents the simulation results; finally, the conclusions and suggestions for future research are summarized in Section 6.

2. Brief Introduction to Dynamic Positioning

The first generation of dynamic positioning (DP) systems came into existence in the 1960's [12]. *Cuss I* and *Eureka* were among the first ships equipped with DP capabilities. A DP system maintains a vessel's position and heading automatically by using its own propellers and thrusters. The control algorithm in a DP system computes appropriate thruster commands for a vessel based on measurements of the ship's position so as to maintain a desired position, or move along a predefined route at sea. A DP system utilizes the ship propulsion and manoeuvring system to provide the necessary actuation to achieve its goal. The very first attempt to dynamically control the position of a surface ship was through manual control, with the operator observing the information provided by the vessel's radar and sonar systems. Even so, it significantly increased the performance of the manually controlled *Cuss I*. Manual control of *Cuss I* took place before satellite navigation systems were widely available, at a time when positioning relied on taut wire mechanisms. The latter are conceptually simple mechanically based positioning-reference systems used to dynamically position a vessel by measuring its position relative to a weight clump on the seafloor in water depths up to 500 metres. Their main limiting factors are: the wire sag effect (or catenary effect) due to the weight of the wire, sea currents, and the ability to maintain a constant tension in the wires.

Eureka, the first "true" DP capable surface ship, utilized singe-input single-output (SISO) analogue controllers to control each of the actuated motions. While DP systems were originally developed as a response to the need for deeper offshore drilling applications, nowadays DP systems are used in a vast range of vessel types, and in different marine operations, such as hydrographic surveying, marine construction, wreck investigation, underwater recovery, site surveying, underwater cable and pipe laying, and inspection and maintenance.

Early DP systems were implemented using PID controllers. To remove the wave-induced motion components from the feedback loop, notch filters in cascade with low pass filters were used with these controllers. Later, the application of advanced control techniques based on optimal control and Kalman filter theory to DP systems led to performance improvement; see [13, 14]. In the 1990s, more advanced nonlinear control techniques such as feedback linearization and backstepping [15] were proposed. Further contributions to observer design followed in [16] and [17], where passivity in combination with adaptive wave filtering were used to reduce the complexity of the implemented control system. Further developments in recent years have led to the use of robust control [18, 19, 20] adaptive control [21, 22, 23, 24, 25] and hybrid control [26] in the design of DP systems. The literature on ship DP is vast and defies a simple summary. See for example [27, 28, 29] and the references therein for extensive summaries of the subject and its historical evolution.

To the best of our knowledge, virtually all DP controllers reported in the literature are based on model based design techniques, though there are exceptions, such as [30]. However, in recent years data-driven control has emerged as an alternative to model based design techniques. This approach makes no assumptions on the structure of the controlled plant, thus avoiding model-mismatch between a design model and the real plant that could lead to performance deterioration, and in the worst case, instability. *Unfalsified control theory* is a data-driven, model-free, adaptive control methodology that allows for controller adaptation by using physical data (input and output measurements of the system) via a process of elimination, much like the candidate elimination algorithm in [31]. Unfalsified control theory may be applied when the plant is either unknown or is only partially known. It consists of two main components: a rich bank of candidate controllers and a falsification technique which uses information from measurements to eliminate the candidate controllers which do not meet the design performance criteria; see [9], [32], [33], [34], [35], [36], [37], [38] and [39] for details on unfalsified control theory.

Following a brief introduction to the foundations of a model-free data-driven control methodology, we propose a dynamic positioning controller that identifies control laws that are consistent with the designer's predefined performance objective and past experimental data. We will further study how we can assess the potential performance of a controller without it being inserted into the feedback loop, based only on plant input-output experimental data. This approach provides a unique opportunity to devise a new strategy for controlling a ship in DP operation, solely on the basis of plant input-output data. The proposed

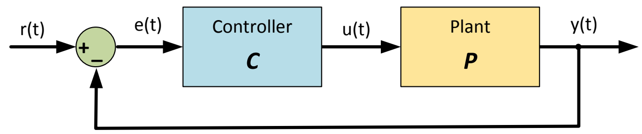

Figure 1: A simple feedback system.

adaptive structure of the controller enables the DP system to operate under different environmental conditions by automatically falsifying controllers that do not meet the performance criteria, and eventually selecting the controller that provides the required performance, removing the human element from all but the top level of the hierarchical DP control structure. Numerical simulations show how a destabilizing controller is detected and replaced by one that is able to meet the designed performance specification.

3. Data Driven Control methodology

In the search for an all-year-round DP system, it is necessary for the system to adapt to changes in working conditions. As the system changes, it might be hard to find a plant model that truly reflects all important aspects of the system; this is in particular true for DP systems in extreme sea conditions where a model-free data-driven unfalsified control can be applied for higher performance.

In this section we briefly review the main aspects of unfalsified control theory. The reader is referred to [39] for further details. The unfalsified control methodology is a direct adaptive switching concept where only measured data are used to assess the performance of a controllers in and out of the feedback loop; for the controllers out of the feedback loop, this is achieved by simultaneously evaluating the performance of all candidate controllers in real time as if they were inserted in the loop thanks to the use of the virtual reference concept.

Consider the simple SISO closed loop system of Fig. 1. The system consists of a linear controller C, and a linear plant P with an input reference $r(t)$, control signal $u(t)$, and process output $y(t)$. Assume that without having access to a model of the plant we wish to assign a performance index to the controller that captures how well it performs using the known and measurable signals u, y and r. Consider the 3-tuples of signals $(r(\cdot), u(\cdot), y(\cdot))$ as a relation in $\mathcal{R} \times \mathcal{U} \times \mathcal{Y}$. Further define the plant and controller as operators such that if $P : \mathcal{U} \to \mathcal{Y}$ and $C : \mathcal{E} \to \mathcal{U}$ then

$$P = \{(u, y) \mid y = Pu\} \tag{1}$$

$$C = \{(e, u) \mid u = Ce\}, \tag{2}$$

where $e = r - y$. Furthermore, let $J(r, u, y)$ be a cost-function that evaluates the performance of the controller in the loop; see [39] for a description how such a cost function can be found. Then, a performance specification P_{spec} can be defined in terms of the set

$$P_{\text{spec}} = \{(r, u, y) \mid J(r, u, y) \leq \rho\}, \tag{3}$$

where ρ is some constant threshold. Consider the simple system presented in Fig. 1 and assume that we have measured the signals $(r(\cdot), u(\cdot), y(\cdot))$ over the time interval $[0\ \tau]$ for a given time τ. Using the time truncation operator

$$u_\tau(t) = f(u(\cdot), \tau) = \begin{cases} u(t) & t \leq \tau \\ 0 & t > \tau \end{cases} \tag{4}$$

we say the measured data set is consistent (or the consistency of data is preserved) when the controller in the loop produces the output

$$u_\tau = C(r_\tau - y_\tau), \tag{5}$$

which in turn produces the system response

$$y_\tau = P\, u_\tau. \tag{6}$$

One can simply assess the performance of the controller C by evaluating the value of the cost function $J(r_\tau, u_\tau, y_\tau)$.

At this stage, we would like to take the discussion one step further and ask the question whether it is possible to use the measured data (u_τ, y_τ) to assess the performance of some other controller C_i $(C_i \neq C)$. Before answering this question, let us emphasize that the unfalsified control methodology includes a rich set of controllers. The bank of controllers admits a set of candidate controllers, $\mathbb{K}$, available for the closed loop system. It is necessary that at least one controller in the bank should be able to meet the desired performance specification in (3).

The consistency of measured data set (r_τ, u_τ, y_τ) is preserved only when the data set is measured during the time interval in which the controller $C \in \mathbb{K}$ was the active controller in the feedback loop. Any controller in $\mathbb{K}$ other than the currently active (in the feed-back loop) controller would have produced a different input-output pair for the same reference signal r_τ; that is the data set (r_τ, u_τ, y_τ) would not be consistent. In what follows, in order to build a consistent data set from a measured input-output pair (u_τ, y_τ), for each controller $C_i \in \mathbb{K}$, a fictitious reference signal $\tilde{r}_i$ is introduced. Let the data (u_τ, y_τ) be the input and output measurements of plant P in Fig. 1 over the time interval $[0\ \tau]$ (when the controller C was the active controller in the feedback loop). Then, we define the fictitious reference signal $\tilde{r}_i$ associated with the controller C_i as an imaginary reference signal that would produce the same data (u_τ, y_τ) if C_i were the active controller in the feedback loop during the data measurement. If the controller C_i is stably causally left invertible (SCLI), then the fictitious reference is realized as

$$\tilde{r}_i = C_i^{-1} u_\tau + y_\tau. \tag{7}$$

Consider now an imaginary scenario where C_i is in the feedback loop and we apply the $\tilde{r}_i$ in (7) as the reference signal; it is easy to verify that this imaginary scenario will lead to the same data (u_τ, y_τ) over the time interval $[0\ \tau]$, and hence, the data set $(\tilde{r}_i, u_\tau, y_\tau)$ is consistent with controller C_i and plant P. In order to assess the performance of the controller C_i using the data set (u_τ, y_τ) that was collected when controller C was in the loop, it is sufficient to evaluate the value of $J(\tilde{r}_i, u_\tau, y_\tau)$.

The restrictive SCLI condition for the candidate controllers is lifted in [40] using matrix fraction description method. This extension allows wider class of candidate controllers be used in the unfalsified control framework.

Using the aforementioned circle of ideas, we can answer the question above and conclude that under certain conditions, it is possible to use the measured data (u_τ, y_τ) (which was measured when the controller C was in the loop) to assess the performance of some other controller C_i ($C_i \neq C$). For LTI controllers, causal left invertibility means these controllers should be both minimum phase and biproper.

The fictitious reference signal is generated for all controllers at each time step such that a consistent data set $Z_i = (\tilde{r}_i, u_\tau, y_\tau)$ exists for all candidate controllers. Z_i is used to calculate the associated cost $J(Z_i)$ with all controllers on-line.

At each sampling time, the measured input and output signals are used to evaluate the performance of the active controller in the loop as well as all the unfalsified controllers in the bank. As soon as any controller violates the design performance requirement, it is falsified and removed from the bank. If the active controller is falsified, then it will be switched off the feedback loop and one of the unfalsified controllers (for example, the one with the lowest cost value) is inserted in the feedback loop. Using this procedure, the bank of the candidate unfalsified controllers diminished over time and eventually a controller that meets the performance criteria is selected.

Switching among controllers happens at discrete time instances when the cost of the currently active controller exceeds a predefined limit, known as the falsification limit ρ. Whenever a controller cost exceeds this limit, the controller is said to be falsified by the previous data and no longer meets the predefined performance specification. When a controller in the bank of controllers $\mathbb{K}$ is falsified, it is removed from set of candidate controllers in $\mathbb{K}$. If an active controller in the feedback loop is falsified, it will be switched off and the new controller $\hat{C}$, at switching time $t^\star$ is found to be one that minimizes the cost among the *as of yet* unfalsified controllers, that is,

$$\hat{C} = \arg\min_{C_i \in \mathbb{K}_{unf}} J(Z_i) \tag{8}$$

where $\mathbb{K}_{unf}$ is the set of unfalsified controllers at time $t^\star$ and (Z_i) is the cost associated with controller C_i at time $t^\star$ using $\tilde{r}_i$.

In what follows, the falsification algorithm is presented for a fixed time step of Δt and a counting variable k.

Initialization:

1. Initialize the finite sets $\mathbb{K}_{unf} = \mathbb{K} = \{C_1, C_2, ..., C_n\}$, $k = 0$, and $\tau = k\Delta t$.
2. For each controller $C_i \in \mathbb{K}_{unf}$, initialize $J(Z_i) = 0$.
3. Select the initial active controller from $\mathbb{K}_{unf}$ by means of any algorithm (can be random).

Real-Time:

1. Let $k \leftarrow k + 1$, $\tau \leftarrow k\Delta t$.
2. Measure $u(t)$ and $y(t)$ and calculate $\tilde{r}_i$ for each controller in $\mathbb{K}_{unf}$ and form $Z_i = (\tilde{r}_i, u_\tau, y_\tau)$.
3. Calculate $J(Z_i)$ for each controller $C_i \in \mathbb{K}_{unf}$.
4. For each controller $C_i \in \mathbb{K}_{unf}$, if $J(Z_i) > \rho$, then falsify the controller C_i and remove it from the $\mathbb{K}_{unf}$.
5. For active controller $\hat{C}$ evaluate $J(Z)$. If $J(Z) > \rho$, then falsify the active controller and select the new active controller from the controllers in $\mathbb{K}_{unf}$ such that

$$\hat{C} = \arg\min_{C_i \in \mathbb{K}_{unf}} J(Z_i).$$

   Otherwise, keep the active controller unchanged.
6. Wait for Δt, and return to step 1.

To summarize, the unfalsified control methodology provides a systematic way to falsify the candidate controllers by computing an intersection of certain sets. A noteworthy feature in this technique is that a controller does not need to be in the loop to be falsified and candidate controllers can even be falsified using data acquired while other controllers were in the loop or even open-loop plant data.

4. Simulation model

In this section, we will present the simulation model for a surface ship in DP operation, Cybership II [20, 41], subjected to changing environmental conditions. The bank of controllers consists of PID controllers with different possible gains for proportional, derivative, and integral terms. At this point, we would like to emphasize that the model presented here is only used for simulation of the presented unfalsified control technique and the plant model is not used in any way for building the bank of controllers. The data driven adaptive control should be able to find appropriate gains (self-tuning) for the current sea state and change the gains to higher performance controller when the environmental load changes. All simulations are carried out using MatLab and Simulink. The basis for the simulation model is adopted from the self-tuning PID controller presented in [33] and available through [42]. However, the methodology presented in [42] is further updated for the purpose of tuning the DP system with varying environmental conditions.

4.1. Ship model

To assess the performance of unfalsified control techniques in station keeping maneuvers we use a three Degree of Freedom (DOF) model for a representative vessel in surge, sway and yaw [43]. These motions are all assumed to be actuated by the ship's thrusters. The ship's model adopted in the simulations has the realization

$$\dot{\xi} = A_\omega \xi + E w_1 \tag{9}$$

$$\eta_w = C_\omega \xi \tag{10}$$

$$\dot{\eta}_{lf} = R(\psi)\nu \tag{11}$$

$$M\dot{\nu} + D\nu = \tau \tag{12}$$

$$\eta = \eta_w + \eta_{lf} \tag{13}$$

Eqns. (9) and (10) capture the 1st order wave induced motions of the ship, i.e. wave frequency motions. Vector $\eta_w \in \mathbb{R}^3$ represents the wave frequency position vector of the ship, where

$$\begin{aligned} A_\omega &= \begin{bmatrix} 0_{3x3} & I_{3x3} \\ -\Omega_{3x3} & -\Lambda_{3x3} \end{bmatrix}, \quad E = \begin{bmatrix} 0_{3x1} \\ I_{3x1} \end{bmatrix} \\ C_\omega &= \begin{bmatrix} 0_{3x3} & I_{3x3} \end{bmatrix}. \end{aligned}$$

with

$$\begin{aligned} \Omega_{3x3} &= \mathrm{diag}(\omega_{01}, \omega_{02}, \omega_{03}) \\ \Lambda_{3x3} &= \mathrm{diag}(2\zeta_1\omega_{01}, 2\zeta_2\omega_{02}, 2\zeta_3\omega_{03}) \end{aligned}$$

as the dominating wave frequencies and damping ratios in the earth-fixed frame. Eqns. (11) and (12) capture the low-frequency motions of the ship and Eqn. (13) gives the total motion of the ship that consists of both wave frequency and low frequency motions. In the above realization, $\eta \in \mathbb{R}^3$ is defined as the extended position vector $\eta = [N, E, \psi]$ where N and E are north-east position in a earth-fixed coordinate frame and ψ, known as heading of the ship, is the angle in the horizontal plane between north-axis and the x-axis of the ship. $\nu \in \mathbb{R}^3$ is the ship velocity vector in a body-fixed coordinate frame and $R(\psi)$ is the orthogonal yaw rotation matrix that relates the earth- and body-fixed frames. In Eqn. (12) $M \in \mathbb{R}^{3\times3}$ and $D \in \mathbb{R}^{3\times3}$ are the generalized mass and linear damping matrices respectively and $\tau \in \mathbb{R}^3$ is the combined forces and moment acting on the model. The extended force vector τ is decomposed into the control vector and forces from wind excitation, i.e. $\tau = \tau_{control} + \tau_{wind}$. Both Coriolis and centripetal accelerations are omitted from the model as the velocities are assumed to be small in DP operations.

4.2. Control and adaptive algorithm

For simplicity, in the current paper three SISO PID controllers are used to control surge, sway, and yaw. Each PID controller is both biproper and minimum phase. The controllers admit the realization in the frequency domain

$$\begin{aligned} e(s) &= r(s) - y(s), \\ u(s) &= K_p e(s) + \frac{K_i}{s} e(s) - \frac{sK_d}{\varepsilon s + 1} y(s), \end{aligned} \tag{14}$$

where s is the Laplace operator, K_p, K_i, and K_d are proportional, integral, and derivative gains, respectively, and $\varepsilon > 0$ is the low pass filter parameter. Reordering the proportional, integral, and derivative terms, according to their input signals, we rearrange the linear PID controller as

$$C_i(s) = [K_p + \frac{K_i}{s}, \frac{sK_d}{\varepsilon s + 1}] =: \left[C_{1,i}(s), C_{2,i}(s)\right], \tag{15}$$

so that

$$u(s) = C_{1,i}(s)e(s) - C_{2,i}(s)y(s). \tag{16}$$

Furthermore, each controller C_i is parameterized by the gains K_p, K_i and K_d. The total candidate controller set is defined as $\mathbb{K} : \mathbb{K}_p \times \mathbb{K}_i \times \mathbb{K}_d$, where $K_p \in \mathbb{K}_p$, $K_i \in \mathbb{K}_i$, and $K_d \in \mathbb{K}_d$.

With the PID structure introduced in (15) and (16), the fictitious reference signal for the *i-th* controller is given by

$$\tilde{r}_i(s) = C_{1,i}(s)^{-1}(u(s) + C_{2,i}(s)y(s)) + y(s). \tag{17}$$

Each candidate controller is associated with a cost value that is continuously compared to the falsification limit ρ. The cost function is selected as

$$J(Z_i) = -\rho + \int_0^\tau e^{-\alpha(t-\tau)} \mu(Z_i) dt, \tag{18}$$

where ρ is a constant used to compensate non zero initial conditions, α is a forgetting factor, and the performance index $\mu(Z_i)$ is a function of time defined as

$$\mu(Z_i) = |w_1 * (\tilde{r}_i - y_\tau)|^2 + |w_2 * u_\tau|^2 - \sigma^2 - |\tilde{r}_i|^2. \tag{19}$$

In the above equation $*$ denotes the convolution operator, σ is a constant used to compensate for the root mean square effects of disturbances, and w_1 and w_2

are shaping filters selected as[1]

$$w_1 = \frac{s+20}{2s+6}, \text{ and } w_2 = \frac{0.01}{1.2(s^3+3s^2+3s+1)}. \tag{20}$$

A controller C_i meets the performance specification (and hence, is unfalsified) if

$$J(Z_i) \leq \rho. \tag{21}$$

The selection of the cost function in the presented data driven adaptive control structure is of extreme importance. The cost function should not only capture the performance of the controllers, but also rapidly show the effect of any destabilizing controllers. The reader is referred to [39] for detailed properties of the cost function.

Switching among the controllers takes place whenever the current active controller gets falsified. Whenever switching happens, a new controller is chosen from the set of controllers that are *as of yet* not falsified (i.e. unfalsified), $\hat{C} \in \mathbb{K}_{unf}$. Note that unfalsified controllers in the bank of controllers can be falsified at any time without the need for replacing the active controller in the closed-loop. If a controller that is not the active controller is no longer consistent with the performance specification, then the set of unfalsified controllers will be updated, and the number of remaining controllers in the bank will be reduced. In fact, as all controllers are evaluated on-line using the fictitious reference signal, this is expected to happen more often than controller switching.

4.3. Environmental loads

Environmental forces and torques included in the model are due to wind and waves. In our simulations, we considered is composed of contact mean and a slowly varying components. Furthermore, the direction of the wind is slowly varying. The contribution of the wind to the total force and torque acting on

[1]See [39] for how to select shaping filters.

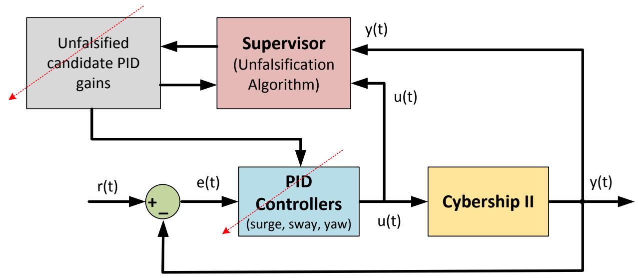

Figure 2: Data-Driven Dynamic positioning Simulator for Cybership II

the ship is computed as

$$\tau_{wind} = \frac{1}{2}\rho_a \begin{bmatrix} -C_X cos(\gamma_w) A_{Fw} \\ C_Y sin(\gamma_w) A_{Lw} \\ C_N sin(2\gamma_w) A_{Lw} L_{oa} \end{bmatrix} V_w^2 \tag{22}$$

where ρ_a is the air density, L_{oa} is length overall, and A_{Fw} and A_{Lw} are the frontal and lateral projected areas, respectively. The angle of attack $\gamma_w =$ is given by $\gamma_w = \psi - \beta_w + \pi$, where ψ is the heading of the ship and β_w is the wind direction. Finally, C_X, C_Y, and C_N are the simplified longitudinal force coefficient, lateral force coefficient, and yaw moment coefficient, respectively [44].

5. Numerical Simulations

Fig. 2 shows the structure of the proposed data-driven model-free DP controller. The results presented here are from a station keeping simulation and an initial condition set of $\eta = [0.1, 0, 0]$. The controller sets were chosen to demonstrate how a destabilizing behavior is detected in both surge and sway and how performance is improved in heading control. The set of candidate controllers used in the simulation are

- Surge

$$Kp = \{10, 100\}, \quad Ki = \{5, 20\}, \quad Kd = \{15, 20\}. \tag{23}$$

- Sway

$$Kp = \{10, 150\}, \quad Ki = \{5, 10\}, \quad Kd = \{5, 10\}. \tag{24}$$

- Yaw

$$Kp = \{5, 10, 20\}, \quad Ki = \{1, 8\}, \quad Kd = \{5, 10\}. \tag{25}$$

The performance specification from Eqn. (19) is used for all three motions with the same filters, defined in Eqn. (20). The constant ρ is chosen to be 0.1, 0.5 and 0.2 for surge, sway and yaw, respectively.

During the simulation, the vessel is excited by waves and wind. The waves are applied to the vessel from the beginning of the simulation while mean wind and a slowly varying component of wind are applied after 50 and 70 seconds, respectively; see Fig. 4. As can be seen in Fig. 5, before the wind is introduced, all three falsification algorithms have changed the controllers at least once to what is considered a stabilizing DP controller.

Fig. 3 shows the vessel's response and the control effort in surge, sway, and yaw. Fig. 4 shows how the environmental forces evolve with time and finally, Fig. 5 shows how and when all three gains of each individual controller change.

The simulation presented in Fig. 3, 4 and 5 illustrate how the proposed data-driven model-free adaptive algorithm is capable of detecting a destabilizing controller during a DP operation without prior knowledge of the plant model and adapting the controllers to provide good performance as the environmental condition changes.

In our opinion, it is important that research in the field marine control systems will take advantage of and exploit increasingly easier access to onboard to onboard measurements, thanks to both smart sensor technology and increasing computation powered installed onboard marine systems. We hope that this brief incursion in the area of data-driven control, supported by numerical simulations, will be beneficial in highlighting the benefits of exploring new perspectives on how data and computational power can improve the performance of marine control systems.

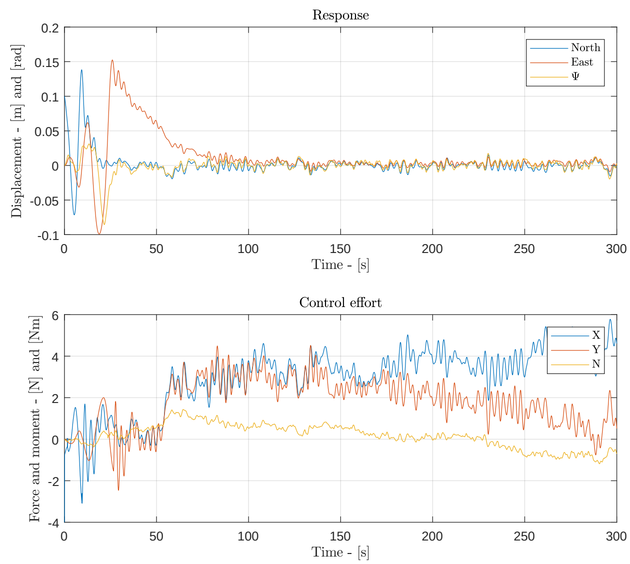

Figure 3: Vessel response in surge, sway and yaw in DP-operation

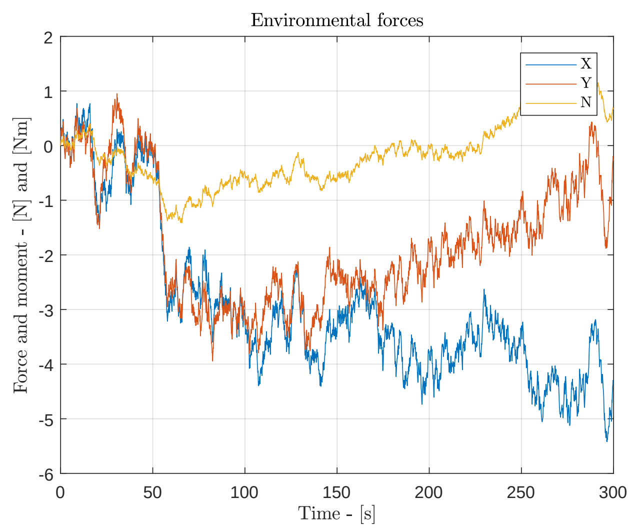

Figure 4: External environmental forces acting on the ship

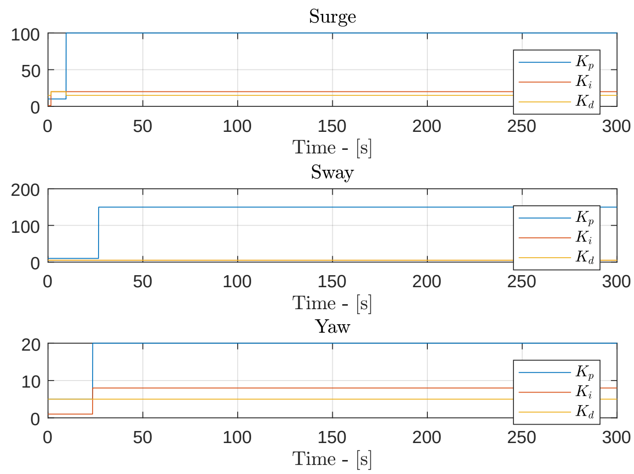

Figure 5: Active controller gains

6. Conclusions and suggestions for future work

We presented the application of a data-driven model-free adaptive control techniques to the problem of dynamic positioning. The control methodology adopted builds upon unfalsified control techniques. Numerical simulations showed that the proposed control structure holds promise for the implementation of Dynamic Positioning Systems for marine vessels subjected to changing environmental forces. The result presented in this article is far from comprehensive. However, we expect that this work will contribute to bring the attention of researchers in the field of marine control to the potential benefits of using data to directly control marine systems without a need to develop a full scale dynamic model. The study aimed to present a new perspective and share some preliminary thoughts on how easy access to measured data in marine systems could change the controller design procedures.

Future reserach will include the extension of the work to multivariate PID control structure and experiments in model scale tests to further document the potential benefits of model-free data based control.

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