Full-scale identification by use of self-oscillations for overactuated marine surface vehicles

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SUMMARY

Controller tuning and state estimation both benefit from knowledge about the dynamic parameters of the marine vessel. However, identifying these parameters can be a daunting task requiring precise open-loop measurements or collection of many output data samples induced by persistently exciting inputs. Performing these experiments in real-life conditions, every time payload of the vehicle changes, can be troublesome. Additional problems appear if the vessel is overactuated. This paper focuses on thruster modelling, actuator allocation and dynamic model identification for an overactuated marine vehicle. Firstly, we demonstrate a practical approach to mapping thrusters of an overactuated marine vehicle that in practice can generate different thrusts at identical inputs. Secondly, we address the issue of inverse actuator allocation for an overactuated surface marine platform and demonstrate a daisy-chain approach for achieving proper thrust distribution during simultaneous motion in all controllable degrees of freedom (DoF). Finally, we describe the application of a robust identification by use of self-oscillations (IS-O) method to identify actuated DoF. While previous work focused on using IS-O for identifying yaw DoF of a rudder-actuated autonomous catamaran and thruster-actuated micro-remotely operated underwater vehicle, in this paper, we extend the approach to identifying surge and sway DoF. This closed-loop identification procedure requires one experiment with four to five oscillations to completely identify inertial and nonlinear drag parameters of a marine vessel. Surge, sway and yaw DoFs of an overactuated autonomous surface marine vehicle PlaDyPos (developed at the Laboratory for Underwater Systems and Technologies) were identified using the IS-O method during sea trials in real-life conditions. Multiple experiments with varying initial settings were performed showing reproducibility of the identification procedure. Comparison of the results with the ordinary least squares identification procedure shows that root mean square error increase is negligible, especially if simplicity (explicit formulae for calculation of unknown parameters) and time parsimony of the IS-O method are taken into account. © 2016 The Authors. International Journal of Adaptive Control and Signal Processing Published by John Wiley & Sons, Ltd.

Received 8 November 2014; Revised 25 June 2016; Accepted 11 July 2016

KEY WORDS: model identification; autonomous surface platform; daisy-chain allocation; thruster mapping; self oscillations

1. INTRODUCTION

The number of autonomous marine vehicles, both underwater and surface, is increasing on a daily basis, and it is expected that this trend will continue. Even on a political level, it is clear that requirements for advanced marine robotics exist. For example, according to the European Union water directive, underwater environmental and habitat monitoring is obligatory to all European Union member states that are making increasing efforts to meet these requirements – this naturally implies exploiting new marine technologies.

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While initial applications of marine robotics were limited to marine surveys and mapping ([1]), recently more emphasis is put on executing advanced tasks, such as intervention ([2]), interaction ([3]) and cognitive reactivity. These can only be accomplished by the development of marine robots with new designs that allow execution of high-level tasks. One such novelty includes the development of overactuated marine vehicles that allow omnidirectional motion. One of the earliest examples of a highly maneuverable underwater vehicles is the Omni-Directional Intelligent Navigator, an autonomous underwater vehicle developed at the University of Hawaii at Manoa [4]. With its reconfigurable thruster configuration, the Omni-Directional Intelligent Navigator is capable of performing motion in up to three degrees of freedom (DoF) at the same time. Recently, it has become a trend to place additional, lateral thrusters on underwater vehicles to increase their manoeuvrability. Some recent examples of such vehicles include SPARUS, [5], developed by the University of Girona, and MEDUSA by the Instituto Superior Tecnico in Lisabon. There is a much smaller number of autonomous surface marine platforms that exhibit omnidirectional behaviour. One of such is PlaDyPos, a vehicle developed by the University of Zagreb, which will be used as a case study in this paper. More details about PlaDyPos are available in [6].

Higher maneuverability and omnidirectional behaviour necessarily lead to more complex control, guidance and navigation algorithms. However, in order to achieve these, proper identification has to be performed. Because small-scale autonomous marine vehicles often have different payload, depending on the specific task that they are required to execute, their dynamic parameters change, and a quick and reliable identification procedure that is applicable in field conditions is required. Classical identification methods that require a large data set to determine model parameters, are often not applicable in real-life conditions. This is why the authors proposed in [7] a fast identification method, applicable in field conditions, that is based on self-oscillations. The method focuses on a time-parsimonious experiment (performed within tens of seconds) where a specific DoF is excited so that self-oscillations, a characteristic behaviour for closed-loop control systems with nonlinear elements, are obtained. Once the magnitude and frequency are acquired, unknown dynamic model parameters are determined by using a set of explicit formulae. The method is referred to as identification by use of self-oscillations (IS-O). The authors have successfully used this method on marine vehicles of different sizes: a micro-remotely operated underwater vehicle (ROV) VideoRay, mid-scale autonomous catamaran Charlie (by the Institute of Intelligent Systems for Automation at the National Research Council of Italy), large-scale ROV LATIS (by the University of Limerick), work-class ROV by LDTravOcean, and so on. For the first time, this paper reports the application of the developed IS-O method on all controllable DoFs (surge, sway and yaw) of an overactuated, omnidirectional, autonomous surface marine platform PlaDyPos.

1.1. Related work on model parameter identification

By design, ships exhibit coupled motion, making the model parameter identification problematic. Precise measurements for coupled model estimation can be performed on scaled models and small unmanned vessels in laboratory conditions. However, detailed models are also required in full-scale and/or manned ships where laboratory conditions are not available.

Low-frequency ship dynamics for uncoupled surge and coupled sway–yaw movement is identified in [8]. The identification method, performed offline, utilizes a extended Kalman filter augmented with unknown parameters. The identified parameters include damping terms and thrust force coefficients. Added mass terms are calculated a priori rather than identified. The identified model was validated in a model-based Dynamic positioning ship controller. Coupled model identification for ship manoeuvring and roll DoF is presented in [9] where a coupled model containing 31 parameters is defined. While some parameters can be calculated with some certainty, the remaining 21 hydrodynamic parameters are identified using the simulated annealing random search algorithm. The minimization method showed good performance even in presence of local minima at cost of slow convergence. This method was applied for system identification in [10] where the dynamic models for scaled and full-scale container ship are compared. The number of parameters to be identified is an important quantity ([9]). Therefore, avoiding overmodelling or undermodelling is necessary. Model structure selection is proposed in [11] where multiple models with increased complexity are
statistically compared and the best fit selected. This first step, where initial parameter estimation is performed, is followed by a second step: an unscented Kalman filter for estimation and prediction error method for parameter refinement. The method focuses on damping terms estimation, and a Monte Carlo study is used to validate the robustness of the approach. Online parameter identification for ship dynamics is proposed in [12]. The recursive algorithm estimates the parameters of the multi-variable auto-regressive exogenous model rather than the usual state-space model. The parameter estimation is validated in simulation and on a training vessel, providing the benefit of parameter adaptation to changes in the environment.

Parameter identification in underwater robotics, similarly to ship identification, is usually performed offline. Often, smaller vehicles are modelled, and the common approach is to apply least-squares estimation of a coupled or uncoupled model to a pre-recorded data set. Identification of a decoupled model for an ROV is found in [13]. Comparison of ordinary least-squares (OLS) and total least-squares for a coupled 3D parameter identification is reported in [14]. This is extended to the full six-DoF coupled model in [15]. The identification in both is performed offline from free-motion data. While offline identification offers more options and techniques, online procedures have the advantage of in-field adaptation to parameter changes. An adaptive technique, implementable online, is proposed in [16] and compared with the common least-squares approach. In [17], the authors report the use of recursive least-squares for online identification of a torpedo-shaped autonomous underwater vehicle. Online parameter identification of a coupled 6-DoF model using a global derivative-free optimization algorithm is proposed in [18]. Often, these techniques require persistent excitation or free-motion data. This in turn requires open-loop control, which might not always be feasible. Additionally, the problem of high sensitivity to noise is encountered by algorithms (e.g. [17]).

Ships and larger autonomous vehicles require identification of a coupled model owing to their size and complexity, which restricts basic assumptions used in smaller vessels. Contrary to ships, open frame ROVs, designed to be symmetric, often actuate controllable DoF in an uncoupled fashion. Additionally, small vehicles allow use of uncoupled models without danger of undermodelling. As mentioned, such vehicles are developed to easily change payload, which noticeably influences parameters and sometimes even hull shape. Applying methods for ship model identification would require use of strip theory for added mass calculation and multiple involved experiments to estimate drag coefficients. Calculation and experiments would need to be calculated for all payload combinations. This approach yields precise models for use in vehicle simulators but minor improvements in control performance.

The proposed identification method allows fast online parameter identification of uncoupled models as an alternative identification approach target at low-overhead controller tuning. The benefit over other approaches is reduced complexity and small computational footprint, allowing implementation in deeply embedded systems. The method is applicable to small underwater and surface vehicles where uncoupled model simplification is justifiable. No a priori knowledge is needed about model parameters, making the proposed method a black-box identification approach compared with the usual gray-box approach where a priori information or estimation is required. However, when coupling effects are pronounced, the method does not perform satisfactorily when compared with coupled model parameter identifications available in the literature.

1.2. Previous work on identification by use of self-oscillations

It is worth mentioning that one of the first papers on system identification and controller tuning using self-oscillations was by Åström and Hägglund in [19], and they were the first ones to introduce a relay as a nonlinear element in the closed loop that would cause self-oscillations. Since then, numerous applications of self-oscillations are reported such as in [20–22], mostly for chemical industry processes.

The first published work of using self-oscillations for identification of marine vehicles was in [23], and it included some heuristical recommendations for underwater vehicle autopilot tuning based on self-oscillation experiments. Since then, many papers have been published with a topic of application of the proposed method on marine underwater and surface vehicles. The most detailed work,
with reported field experiments and validation of the obtained results, can be found in [7]. There, the method of using self-oscillations for the purpose of identification of a general continuous static process of $n$-th order has been described. The methodology was then extended to a static process with time delay. The final modification included the methodology for using the IS-O procedure on discrete time processes. Once the overall framework was described, we focused on the application of the method to marine vehicles, specifically to the identification of the yaw DoF by using pure magnetic compass measurements. Two case studies were observed: identification of a rudder-actuated autonomous surface catamaran Charlie and identification of a small-sized remotely operated vehicle VideoRay, which is actuated by two thrusters in the horizontal plane. The results obtained from more than 120 experiments in real-life conditions that took place during 2 days of trials have led us to the following conclusions:

- the IS-O method provides explicit formulae for calculation of unknown model parameters (inertia and drag) of marine vessels even when the assumed model is nonlinear (when drag parameter is a function of vessel speed),
- the IS-O method gives comparable results with the least-squares identification method but with significant reduction in time and calculation required to obtain the unknown model parameters,
- the IS-O method efficiently takes into account external disturbances that act on the vehicle and compensates their influence,
- the IS-O methodology can easily be applied to determine whether a linear or nonlinear model is more appropriate for describing vehicle dynamics.

1.3. Main contributions

The main contributions of the paper can be summarized as follows:

1. **Application of a two-step inverse allocation for improved utilization of asymmetric thrusters by nonequal distribution of virtual forces moments across thrusters.** In order to improve open-loop behaviour, individual thruster mapping in combination with a two-step daisy-chain approach is used.

2. **Full-scale identification by use of self-oscillations applied to surge, sway and yaw DoF of an overactuated surface marine platform.** In the previous work, the authors have successfully reported the application of the proposed methodology for identifying yaw DoF. Because of high interest of theoretical and practical knowledge, this paper extends the application to all controllable DoFs in the horizontal plane.

The paper is organized as follows. Chapter 2 describes the full kinematic and dynamic model used for marine vehicles, together with simplifications that are often used in control design. Practical aspects of modelling overactuated thruster configurations for marine vehicles are presented in this chapter. In addition to that, a practical example of omnidirectional control with classical inverse allocation and improvement using a two-step inverse allocation approach is given. The identification by use of self-oscillations with aspects of its application to surge and sway DoF of marine vehicles is given in Chapter 3. Full experimental results together with commentaries are presented in Chapter 4. The paper is concluded with Chapter 5.

2. VEHICLE MODELLING

Defining the mathematical model is required to create the overall picture of laws governing the motion of an underwater vehicle. Identification methods can then be developed to identify the parameters that participate in the vehicle dynamics. General rigid-body dynamics and the explanation to underwater vehicles are well defined in [24], from where the naming convention and general terminology throughout the paper are adopted. This section will give a brief overview of the definitions and the general marine vehicle model. Simplifications needed to derive the identification by
self-oscillations will be considered. Finally, propulsion and allocation models required to correctly achieve desired forces are presented.

The marine vehicle dynamics and kinematics can be defined inside the inertial and body reference frames, as shown in Figure 1. The inertial or north–east–down frame, denoted as \( \{E\} \), is the local tangent plane used for navigation. The frame can be treated as inertial owing to slower marine vehicle dynamics. The body-fixed reference frame, denoted as \( \{B\} \), moves with the marine vehicle. The body-fixed frame origin is often defined at the rotational or gravity centre.

Position and orientation, \( \eta = [x \ y \ z \ \phi \ \theta \ \psi] \), are defined in \( \{E\} \), while linear and angular velocities, \( \nu = [u \ v \ w \ p \ q \ r] \), are defined in \( \{B\} \). Vector \( \tau \) defines virtual forces and moments acting on the rigid-body in \( \{B\} \). Controllers commanding \( \tau \) are vehicle independent (generic) because they do not make assumptions about a vehicle’s actuator layout.

2.1. Mathematical model

Relations between velocities and accelerations of the vehicle and forces that act on it are given with a dynamical model in (1), which includes hydrodynamic effects and couplings between motions.

\[
\begin{align*}
\frac{(M_{RB} + M_A)}{M} \ddot{\nu} + (C_{RB}(\nu) + C_A(\nu)) \nu + D(\nu) \nu + g(\eta) = \tau + \tau_\epsilon
\end{align*}
\]

(1)

\[
\dot{\eta} = J(\eta) \dot{\nu}
\]

(2)

where \( M_{RB} \) is the diagonal mass and inertia matrix and \( M_A \) is the added mass matrix that comes from hydrodynamic effects acting on the marine vehicle. \( C_{RB} \) and \( C_A \) are the rigid-body and added Coriolis and centripetal matrix. The damping matrix is denoted as \( D \) and is usually approximated by nonlinear, speed-dependent diagonal terms. Finally, the restoring force, which appears owing to difference between buoyancy and weight of the submerged vehicle, is represented by \( g(\eta) \). Different environmental disturbances acting on the vehicles are combined in \( \tau_\epsilon \).

Equation (1) defines the dynamics in \( \{B\} \). How this dynamics is reflected in the inertial frame is governed by the kinematics equation (2) where the full form of the Jacobian matrix \( J(\eta) \) can be found in [24].

2.2. Model simplifications

Equation (1) contains almost a hundred parameters. Some parameters, for example, mass, centre of gravity and buoyancy, are usually known with good confidence as they can be directly measured. However, added mass and damping terms are harder to measure and calculate. This is especially true for off-diagonal coupling terms that are exhibited only during coupled motion. Identifying or numerically estimating all the parameters could be very demanding and, depending on the task, an overkill. Realistic simulations may require off-diagonal elements and a complex model, but most controllers and estimation filters can also benefit from a simpler uncoupled model.

Model reduction can be achieved by setting the following assumptions:
• the centre of gravity coincides with the origin of the body-fixed coordinate frame
• roll and pitch motions are negligible and the identified DoFs have direct actuation
• the damping matrix is diagonal and can be approximated with a first-order speed-dependant term.

The first assumption is usually satisfied for most underwater vehicles. However, the second assumption forces the vehicle to have uncoupled dynamics. Torpedo-shaped vehicles often control heave through motion coupling with the pitch DoF and violate this assumption. The third assumption forces the vehicle to have three planes of symmetry in addition to uncoupled motion. This constraint is rarely satisfied by marine vehicles, but for non-coupled motions, a diagonal damping matrix gives a good approximation, [25].

These assumptions lead to one, generalized, uncoupled, nonlinear dynamic equation that describes surge, sway, heave and yaw DoF separately:

$$\alpha_v \dot{v}(t) + \beta(v) \cdot v(t) = \Delta + \tau(t)$$

$$\beta(v) = \begin{cases} \beta_v & \text{for constant drag} \\ \beta_{v|v|} |v| & \text{for linear drag} \end{cases}$$

where $v$ is speed in a single DoF; $\alpha_v$, $\beta_v$, $\beta_{v|v|}$ are model parameters; $\tau$ is a single DoF excitation force or moment; and $\Delta$ represents external disturbances and all unmodelled dynamics of the system. Note that for constant drag, the model is linear, while for linear drag, it becomes nonlinear.

The simplified model offers a reduced number of parameters required for identification. The uncoupled equation fits well with standard controller auto-tuning methods providing potential for autonomous in-field tuning. Smaller vehicles, those moving at lower speeds and those that actuate directly the modelled DoFs can be approximated with such simple models. Coupling effects become pronounced at higher speeds and larger vehicles where the simplified model cannot be applied. However, in such cases, the simplified model can still be of use for initial controller tuning.

2.3. Propulsion modelling

The main inputs in marine vehicle dynamics model are the virtual forces and moments $\tau$ that are used by identification and control algorithms to excite the vehicle. However, the general model does not incorporate the propulsion system, which is a crucial part in creating the desired force. The control and identification algorithms treat the vehicle itself as a black-box and are unaware of the propulsion subsystem. Vehicle dynamics and kinematics model can be expanded with the propulsion model as shown in Figure 2.

In addition to the described vehicle dynamics and kinematics, Figure 2 introduces the nonlinear actuator mapping $h(n)$ and allocation map $\Phi(F)$. Nonlinear actuator mapping is a static map that describes what force or moment, $F_i$, is generated by a single actuator given an input $n_i$. The allocation map, on the other hand, transforms the actuator forces and moments into virtual forces and moments used in the mathematical model of the vehicle.

The thrust produced by an asymmetrical fixed position thruster is given with [26],

$$F_i = h(n_i) = \begin{cases} K^+ n_i |n_i| & \text{for } n_i \geq 0 \\ K^- n_i |n_i| & \text{for } n_i < 0 \end{cases}$$

Figure 2. Marine vehicle allocation model. [Colour figure can be viewed at wileyonlinelibrary.com]
Table I. Thruster gain parameters.

| Thruster | $K^*$  | $R^2$ |
|----------|--------|-------|
| $T_1$    | + 6.75 | 0.992 |
| $T_1$    | + 5.20 | 0.947 |
| $T_2$    | + 8.39 | 0.991 |
| $T_2$    | + 3.29 | 0.985 |
| $T_3$    | + 9.97 | 0.994 |
| $T_3$    | + 4.17 | 0.964 |
| $T_4$    | + 8.86 | 0.994 |
| $T_4$    | + 4.21 | 0.982 |

Figure 3. Thruster measurements and fit results. [Colour figure can be viewed at wileyonlinelibrary.com]

where $K^+_i$ and $K^-_i$ are the $i$-th thruster coefficient for positive and negative rotations, respectively. Propeller revolutions per minute are denoted with $n_i$. It should be noted that affine model (5) should be replaced with a bilinear model in case of significant forward speed, that is, water flow through the thruster [24]. Nevertheless, the simpler affine model is often preferred.

Identification of $K_i$ is referred to as thruster mapping. The mapping allows correct compensation of thruster nonlinearities and approximation of achieved static thrust. The thruster mapping results for PlaDyPos are summarized in Table I and Figure 3. Normalized armature voltage was used as the abscissa in Figure 3. Because the thruster is asymmetric, difference between forward and reverse thrust is noticeable. It should also be mentioned that dead zone and Coulomb friction nonlinearities are not incorporated in the fitting model of the thruster.

The mapping determined the static conversion between thruster revolutions per minute and generated force for each individual thruster. Thrust allocation will determine the mapping from individual forces to the generalized forces and moments $\mathbf{\tau}$.

2.4. Thruster allocation

For the PlaDyPos surface platform, the thruster allocation is defined as

$$\mathbf{\tau} = \Phi(F) = \begin{bmatrix} \cos 45^\circ & \cos 45^\circ & -\cos 45^\circ & -\cos 45^\circ \\ \sin 45^\circ & -\sin 45^\circ & \sin 45^\circ & -\sin 45^\circ \\ D & -D & -D & D \end{bmatrix} \mathbf{F}$$

where $\mathbf{B}$ is called the allocation matrix and $\mathbf{F}$ is the vector containing forces $F_i$ exerted by each thruster. $D$ is the lever arm of each thruster around the vertical axis of rotation. Only three DoFs are
controlled (surge, sway and yaw), but four thrusters are available, making the allocation problem overactuated. Usually, the inverse allocation problem is solved using the Moore–Penrose pseudoinverse $B^{-1} = B^T (BB^T)^{-1}$. However, due to thruster saturation, using only the pseudoinverse can result in performance degradation.

Consider an ideal situation where thrusters, placed in X configuration, are identical and symmetrical with normalized thrust $F_i \in [-1, 1]$. The achievable generalized forces region, for surge and sway, is shown in green in Figure 4. As an example, desired tau is taken as $(2, 3, 0)$. The pseudo-inverse calculation gives the thrust $F = (0.35, -1.77, 1.77, -0.35)$. After saturation, this results in the achieved $\tau$, shown in green. The achieved vector fails to preserve the desired direction of the forces. Therefore, a scaling saturation is proposed with $F_{i,\text{achieved}} = F_i \max(F_{i,\text{max}})$, which results in the red virtual thrust vector shown in Figure 4. The desired force direction is now retained.

The drawback of the scaling allocation is that, in presence of a single larger force request (e.g. surge), other small forces become negligible. An illustrative example is shown in Table II where the desired vector $\tau = (20, 5, 0.1)$ cannot be achieved owing to thruster limitations. The scaling approach would result in the achieved vector $\tau_a = (2.26, 0.56, 0.01)^T$ – observe that achieved $N_a = 0.01$ is much lower than the desired $N = 0.1$. Meaning, the heading control will fail. This is a situation that occurs with PlaDyPos – because of its design, a constant small moment $N$ is required to keep the vehicle from rotating while performing translational motion.

To mitigate the effect, a two-step allocation is suggested, similar to the daisy-chain approach. PlaDyPos thrusters are not divided into two groups, as is common in daisy-chain allocations, because they can all work continuously. Instead, a region of yaw moments $N$ that should be achievable is defined, thus allowing room for the yaw moment to assert itself in presence of high surge and sway requests. Therefore, during the first step, the yaw moment is allocated inside of this region. The remaining available region for surge and sway forces is calculated and the pseudo-inverse in combination with the scaling saturation applied.

| Type           | $F$                              | $\tau_a$                           |
|----------------|----------------------------------|------------------------------------|
| Simple         | $(-1.00, -1.00, 1.00, 1.00)^T$    | $(2.82, 0.00, 0.00)^T$             |
| Scaling        | $(-0.59, -1.00, 0.99, 0.60)^T$    | $(2.26, 0.56, 0.01)^T$             |
| Daisy-chain    | $(-0.56, -1.00, 0.95, 0.61)^T$    | $(2.21, 0.55, 0.10)^T$             |

Figure 4. Desired and achieved thrusts due to normal and scaled thruster saturation. The blue line indicates the desired thrust $(2, 3, 0)$, and the green and red lines indicate the resulting saturate and scaled thrusts, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]
Figure 5. Heading control and achieved thrust with (a) direct scaling allocation, (b) two-step allocation. In (a) the yaw moment is virtually nonexistent owing to scaling effects and the controller performance suffers. In (b) the yaw moment is present owing to the two-step approach and heading control is restored. [Colour figure can be viewed at wileyonlinelibrary.com]

The approach with and without the daisy-chain allocation is illustrated in Figure 5. The upper subplots show the desired and actual PlaDyPos heading, while the bottom subplots show the estimated surge, sway and yaw forces achieved by the thrusters. Initially, PlaDyPos holds its position and heading for around 2 min in both figures. Next, a distant position is commanded to the position controller in order to saturate the thrusters with high, unconstrained, surge and sway requests. This happens approximately after 20 s in both figures. Initially, the vehicle heading is positioned favourably in the direction of a single arm (due to hydrodynamic characteristics). Observe that in Figure 5(a), where only scaling allocation is active, the yaw moment appears flatlined owing to the large-scaling factor. The heading remains virtually the same throughout the movement despite the reference changes. In Figure 5(b), the allocation for yaw DoF is performed separately from surge and sway. Notice that the yaw moment is now more active and the heading control is able to perform satisfactorily.

3. IDENTIFICATION BY USE OF SELF-OSCILLATIONS APPLICATION TO MARINE VEHICLES

Identification of process parameters in open-loop is often tedious and time-consuming. If process parameters change in time (owing to time-variant payload, disturbances, environment, etc.), classical identification methods are simply not convenient. In field conditions, it is simply not practical to perform a series of tests that will give a satisfactory set of parameters based on which controllers might be tuned. This was the main motivation for research in the field of identification by use of self-oscillations and its application to marine vehicles. This method, unlike conventional identification methods, is time-parsimonious, easily implementable and applicable in field conditions by non-experts.

Self-oscillations are a stable behaviour characteristic for nonlinear systems, [27], unlike oscillations that arise in linear time-invariant systems, [28]. Even though self-oscillations are often considered a malicious effect in nonlinear control systems, they can be used to determine unknown parameters of a process. In these cases, nonlinear elements are intentionally introduced in the closed loop in order to induce self-oscillations. Self-oscillations in general are defined for a closed-loop system where the static nonlinear element $F(x)$ that induces self-oscillations and general process $x = f(x)$ can be separated as shown in Figure 6. In addition to that, an assumption is made that the process attenuates higher multiples of the principle harmonic of self-oscillations. This assumption is usually satisfied for technical systems owing to their low-pass characteristics.

Let us define a biased monoharmonic signal in a form

$$x(t) = x_0 + X_m \sin \omega t = x_0 + x^*$$  (7)
Figure 6. A closed loop consisting of a static nonlinear element and a generalized process.

and let it be at the input of a static nonlinear element whose output is in the form

\[ y_N(t) = F(x) \]  

where \( F(x) = -F(-x) \) is symmetric.

The output \( y_N(t) \) of the nonlinear element \( F(x) \) can be developed in a Fourier series, and if only the first harmonic of the series is taken into account, the output can be approximated with

\[ y_N(t) \approx Y_0(x_0, X_m) + \left[ P_N(x_0, X_m) + Q_N(x_0, X_m) \frac{P}{\omega} \right] x^* \]  

where \( p = \frac{d}{dt} \) is the differential operator and \( Y_0, P_N \) and \( Q_N \) are parameters of the describing function of the static nonlinear element [27]. It should be mentioned that these parameters depend on the magnitude \( X_m \) and the bias \( x_0 \) of the input monoharmomic signal.

As it was mentioned before, different DoFs of underwater vehicles can be represented with a generalized model in a form given with (3). The first-order process given in (3), where \( y = \dot{v} \) is the measured value and \( \tau \) is input, cannot be introduced to self-oscillations by using a relay with hysteresis. However, if we introduce a new variable, \( \eta = \dot{v} \), the process with the output \( \eta \) and input \( \tau \) becomes a second-order process that exhibits self-oscillations when in closed loop with a relay with hysteresis.

For yaw DoF, it is natural to use \( \eta = \dot{\psi} = \dot{r} \) as output measured directly from the compass. This is in fact a simplified kinematic model that assumes that pitch and roll angles are 0. However, for surge and sway DoF, there does not exist a sensor that directly measures the integral of surge and sway speed. This is why a modification for these two DoFs is introduced in Section 3.1.

If we assume that the drag coefficient is given with \( \beta(v) = \beta_v \cdot |v| \), a nonlinear process in the form given with (10) is obtained

\[ \alpha_v \ddot{\eta} + \beta_{vv} |\dot{\eta}| \dot{\eta} = \tau + \Delta. \]  

If this process is placed in a closed loop with a nonlinear element that can induce self-oscillations, the following set of equations is obtained when (9) is combined with (14), where \( Y_0 = Y_0(x_0, X_m) \), \( P_N = P_N(x_0, X_m) \) and \( Q_N = Q_N(x_0, X_m) \):

\[ \alpha_v X_m (j \omega)^2 \sin(\omega t) + j \beta_{vv} X_m^2 \omega^2 |\sin(\omega t)| \sin(\omega t) = \Delta + [-Y_0 - (P_N + j Q_N) X_m \sin(\omega t)]. \]

Further development of the nonlinear term to the Fourier series gives

\[ |\sin(\omega t)| \sin(\omega t) \approx \frac{3\pi}{8} \sin(\omega t), \]

and finally, three equations that describe the unknown parameters can be written:

\[ \alpha = \frac{P_N(x_0, X_m)}{\omega^2} \]  

\[ \beta_{vv} = -\frac{3\pi}{8} \frac{Q_N(x_0, X_m)}{X_m \omega} \]  

\[ \Delta = Y_0(x_0, X_m). \]  

For the case when drag is given with \( \beta(v) = \beta_v \), the process model (3) becomes

\[ \alpha_v \ddot{\eta} + \beta_v \dot{\eta} = \tau + \Delta. \]
### Table III. Formulae for determining unknown parameters using identification by use of self-oscillations method with relay with hysteresis.

| Linear model (Constant drag) | Nonlinear model (Linear drag) |
|-----------------------------|-------------------------------|
| \( \alpha_u = \frac{P_N(x_0, X_m)}{\omega^2} \) | \( \alpha_u = \frac{2C}{\pi} \frac{1}{\omega^2 X_m} \left[ \sqrt{1 - \left( \frac{x_a - x_0}{X_m} \right)^2} + \sqrt{1 - \left( \frac{x_a + x_0}{X_m} \right)^2} \right] \) |
| \( \beta_u = -\frac{1}{\omega} \frac{Q_N(x_0, X_m)}{\omega} \) | \( \beta_u \) |
| \( \beta_v = -\frac{3\pi}{\omega} \frac{Q_N(x_0, X_m)}{X_m \omega^2} = \frac{3C}{\omega} \frac{1}{\omega^2 X_m^2} \) | \( \beta_v = -\frac{Q_N(x_0, X_m)}{\omega} \) |
| \( \Delta = C \frac{T_H - T_L}{T_H + T_L} \) | \( \Delta \) |

Using the same procedure as described before, we come to the result that parameters \( \alpha_u \) and \( \Delta \) are obtained using the same equations as given with (11) and (13), respectively, while \( \beta_v \) is given with

\[
\beta_v = -\frac{Q_N(x_0, X_m)}{\omega}.
\]

If the nonlinear element that induced the self-oscillations is a relay with hysteresis, with describing function parameters \( P_N(x_0, X_m), Q_N(x_0, X_m) \) and \( Y_0(x_0) \) given with (16), (17) and (18), the terms for identifying unknown parameters for the case of linear and nonlinear process model can be found in Table III, where parameter \( C \) is relay output value, \( x_a \) is half the hysteresis width, \( x_0 \) is bias in self-oscillations, \( X_m \) is amplitude of self-oscillations and \( T_H \) and \( T_L \) are durations of relay high and low output in one period of self-oscillations.

\[
P_N(x_0, X_m) = \frac{2C}{\pi X_m} \left[ \sqrt{1 - \left( \frac{x_a - x_0}{X_m} \right)^2} + \sqrt{1 - \left( \frac{x_a + x_0}{X_m} \right)^2} \right]
\]

\[
Q_N(x_0, X_m) = -\frac{4C}{\pi X_m^2}
\]

\[
Y_0 = C \frac{T_H - T_L}{T_H + T_L}
\]

The following sections will give a detailed description on how to apply the proposed procedure on surge and sway DoF of marine vehicles.

Based on the obtained IS-O experimental data, formulae in Table III can be applied to determine the unknown model parameters. Experimental results of the IS-O method applied on PlaDyPos are presented in Section 4.

#### 3.1. Identifying surge and sway degrees of freedom

For the surge and sway DoF, we can write \( v = u \) and \( v = v \), respectively. Again, processes given in the form

\[
\alpha_u \dot{u} + \beta(u) \cdot u = X + \Delta
\]

\[
\alpha_v \dot{v} + \beta(v) \cdot v = Y + \Delta
\]

cannot exhibit self-oscillations. For the case of surge and sway DoF, the process of applying the IS-O methodology is not straightforward because there does not exist a natural measured variable \( \eta \) with the property \( \dot{\eta} = v \) that can ensure that self-oscillations will be established in the closed loop, as is the case for yaw DoF. Usually, surge and sway speed can be directly measured if a Doppler velocity logger (DVL) is available. However, the same procedure as in the yaw case can be applied...
if an artificial integrator is introduced to the relay input, as it is shown in Figure 7. That way, a new variable \( \eta = \dot{u}^\circ = \int u \, dt \) for surge and \( \eta = \dot{v}^\circ = \int v \, dt \) for sway model are introduced to the relay input, and the two models can be described with (21) and (22). Introducing an extra integrator ensures symmetric self-oscillations around any \( u_{\text{REF}} \) or \( v_{\text{REF}} \) (where usually \( u_{\text{REF}} = v_{\text{REF}} = 0 \)).

\[
\alpha_u \ddot{u}^\circ + \beta (\dot{u}^\circ) \cdot \dot{u}^\circ = X + \Delta \tag{21}
\]

\[
\alpha_v \ddot{v}^\circ + \beta (\dot{v}^\circ) \cdot \dot{v}^\circ = Y + \Delta \tag{22}
\]

Based on the obtained IS-O experimental data, formulae in Table III can be applied (by substituting \( \nu = u \) and \( \nu = v \) for surge and sway DoF, respectively) to determine the unknown model parameters. Experimental results of the IS-O method applied on the vehicles are presented in Section 4.

4. RESULTS

This section gives examples of obtained IS-O experiments for all controllable DoFs on PlaDyPos (yaw, surge and sway), results obtained from multiple IS-O experiments and comparison of the obtained models with the OLS method.

4.1. Examples of identification by use of self-oscillations experiments for yaw, surge and sway degree of freedom

An example of self-oscillations obtained on yaw, surge and sway DoF of PlaDyPos overactuated vehicle is given in Figure 8(a)–(c), respectively. The parameters of the relay with hysteresis for yaw DoF were \( C = 1.5 \), \( x_a = 20^\circ \) and surge and sway DoF \( C = 0.1 \), \( x_a = 0.4m \).

Comment (on the quality of obtained signals)

While yaw DoF results are usually very good owing to the quality of the compass measurements, Figure 8(b) and (c) clearly demonstrates that measurements from the DVL can be quite noisy. Using these raw measurements for identifying the dynamical model by, for example, OLS identification, can be a difficult process, or it would at least require some filtering in order to obtain smooth data. Because the integrator is inherently a low-pass filter, values \( \dot{u}^\circ \) and \( \dot{v}^\circ \) (shown in red) are smooth and extreme values of the oscillations, as well as their frequency can be easily determined.

Comment (on the area required for experiments)

During the yaw identification experiment, it is clear that the vehicle is executing only oscillations around the \( z \)-axis, and ideally, no movement is present in the horizontal plane. Practically, there will be some limited movement due to asymmetries in the vehicle construction. During the surge and sway experiment, the vehicles moves in a confined area defined by the relay characteristics – in the specific case, an area of about 1m\(^2\) is occupied. This clearly demonstrates how the IS-O method requires a very limited area in order to obtain model parameters. From a practical point of view, this is a very convenient feature, unlike in the case of other identification methods where, due to the requirement on the persistent excitement of the input signal, a much larger area may be required to obtain a satisfactory model.
4.2. Full-scale identification by use of self-oscillations experimental results

Extensive experiments in real conditions at the Croatian Navy base in Split were executed in June 2014. All three controllable DoFs were identified using the IS-O methodology with different relay parameters in order to determine consistency of obtained models. For surge and sway DoF, all together, 48 experiments were conducted with relay output varying from $C_D = 0.8$ to $C_D = 2.6$, and with relay width in the range of $x_a = 0.3$ to $x_a = 0.9$ m (with the step of 0.2 m). For yaw DoF, 21 experiments were conducted with relay output in the range $C_D = 0.5$ to $C_D = 2.5$ and relay width from $x_a = 0.17$ to $x_a = 0.34$ rad. Identified parameters for all experiments are shown in Table IV.

Comment (On the consistency of identification by use of self-oscillations method)

In practice, only one IS-O experiment should be conducted to determine the unknown model parameters in a single DoF. However, multiple experiments were conducted in order to test the consistency of the results. In Table IV, it can be seen that inertia parameter $\alpha/E_T$ in surge and sway DoF is identified in different experiments with standard deviation of around 12%, while in yaw case, the deviation is around 4%. Identified drag parameters $\beta_{uv}$ have a deviation of about 10%, while in the yaw model, it is about 23%. Given that fact that the experiments were conducted in real conditions, these results show that the obtained results are consistent with respect to the relay parameters.

Comment (on consistency with the vehicle symmetry)

Ideally, surge and sway model parameters should be the same because the platform is designed to be symmetrical in the horizontal plane. The obtained results shown in Table IV demonstrate that there is little difference between the identified inertia and drag parameters: on average, identified
Table IV. Results of identification by use of self-oscillations applied to surge, sway and yaw DoF.

|       | Surge DOF |       | Sway DOF |       | Yaw DOF |
|-------|-----------|-------|----------|-------|---------|
|       | $x_a$     | $\alpha_x$ | $\beta_{xx}$ | $x_a$ | $\alpha_y$ | $\beta_{yy}$ | $x_a$ | $\alpha_r$ | $\beta_{rr}$ |
| C     | [m]       | [m$^2$/m] | [m$^2$/m$^2$] | C     | [m]       | [m$^2$/m] | [m$^2$/m$^2$] | C     | [deg]     | [rad$^2$/m] |
| 0.8   | 0.3       | 10.76   | 28.68     | 0.3   | 10.53     | 29.58     | 0.17   | 1.80      | 4.48     |
|       | 0.5       | 12.56   | 28.76     | 0.5   | 11.69     | 23.76     | 0.5    | 1.90      | 3.92     |
|       | 0.7       | 12.80   | 23.05     | 0.7   | 12.54     | 24.55     | 0.34   | 1.82      | 3.89     |
|       | 0.9       | 14.13   | 25.53     | 0.9   | 13.17     | 23.77     |        |           |          |
| 1     | 0.3       | 9.84    | 23.82     | 0.3   | 9.38      | 27.18     | 0.17   | 1.98      | 3.92     |
|       | 0.5       | 11.44   | 24.98     | 1     | 0.7       | 10.74     | 23.51  | 0.75      | 1.82      | 3.39     |
|       | 0.7       | 12.94   | 23.71     | 0.7   | 13.31     | 23.80     | 0.34   | 1.71      | 3.75     |
|       | 0.9       | 14.31   | 24.47     | 0.9   | 15.56     | 24.19     |        |           |          |
| 1.4   | 0.3       | 11.29   | 24.03     | 0.3   | 11.19     | 24.84     | 0.17   | 1.86      | 2.99     |
|       | 0.5       | 11.93   | 23.84     | 1.4   | 0.5       | 10.85     | 20.99  | 1         | 2.66      | 2.68     |
|       | 0.7       | 13.41   | 21.37     | 1.4   | 0.7       | 11.12     | 20.33  | 0.34      | 1.84      | 2.95     |
|       | 0.9       | 14.63   | 23.29     | 1.4   | 0.9       | 13.12     | 21.24  |          |           |
| 1.8   | 0.3       | 11.74   | 20.80     | 0.3   | 10.39     | 22.89     | 0.17   | 1.90      | 2.52     |
|       | 0.5       | 12.02   | 23.32     | 1.8   | 0.5       | 11.64     | 19.79  | 1.25      | 1.72      | 3.15     |
|       | 0.7       | 13.51   | 23.98     | 1.8   | 0.7       | 9.99      | 20.57  | 0.34      | 1.86      | 2.90     |
|       | 0.9       | 14.21   | 23.20     | 1.8   | 0.9       | 13.38     | 19.71  |          |           |
| 2.2   | 0.3       | 10.42   | 23.57     | 0.3   | 11.42     | 21.81     | 0.17   | 1.82      | 2.60     |
|       | 0.5       | 11.78   | 22.67     | 2.2   | 0.5       | 10.41     | 23.89  | 1.5       | 1.77      | 2.91     |
|       | 0.7       | 12.11   | 22.50     | 2.2   | 0.7       | 12.38     | 18.75  | 0.34      | 1.78      | 2.95     |
|       | 0.9       | 11.96   | 21.35     | 2.2   | 0.9       | 12.53     | 20.55  |          |           |
| 2.6   | 0.3       | 11.24   | 21.49     | 0.3   | 10.17     | 20.96     | 0.17   | 1.88      | 2.11     |
|       | 0.5       | 10.41   | 22.05     | 2.6   | 0.5       | 11.54     | 19.75  | 2         | 1.80      | 2.58     |
|       | 0.7       | 14.54   | 21.80     | 2.6   | 0.7       | 11.83     | 19.54  | 0.34      | 1.91      | 2.37     |
|       | 0.9       | 15.72   | 22.22     | 2.6   | 0.9       | 12.40     | 20.32  |          |           |

| $\sigma$ | 12.39% | 8.42% | 11.88% | 11.85% | 4.37% | 22.82% |

surge and sway inertias deviate by less than 5%, while drags deviate by less than 4%. This is an informative indicator of the quality of the obtained results.

4.3. Comparison with the least-squares identification

Model parameters obtained by the IS-O method were compared with the model obtained using the OLS method. Parameters obtained using the least-squares method and parameters averaged over all IS-O experiments are given in Table V.

Comment (on similarity between OLS and IS-O obtained parameters)
When comparing model parameters obtained by the OLS method and the IS-O method, we observe that there is greater similarity between the obtained drag parameters than between inertia parameters, even though significant statistical differences are obvious. However, there is reason to take OLS parameters with caution because the difference in the obtained surge and sway model parameters is much higher in comparison with the IS-O surge and sway model parameters. As mentioned before, theoretically, there should not be any difference due to the symmetry of the vehicle in the horizontal plane.

Comparison of the time responses of the models with the IS-O obtained parameters and those obtained using the OLS method are shown in Figure 9 where real measurements for each DoF are shown in green, output of the OLS model is shown in red and outputs of each model obtained with...
Table V. Surge, sway and yaw parameters identified with the IS-O and the OLS.

| Method | Surge DOF | Sway DOF | Yaw DOF |
|--------|-----------|----------|---------|
|        | $\alpha_u$ | $\beta_{uu}$ | $R^2$ | $\alpha_v$ | $\beta_{vv}$ | $R^2$ | $\alpha_r$ | $\beta_{rr}$ | $R^2$ |
| IS-O   | 12.49     | 23.51    | 0.642 | 11.72     | 22.34    | 0.721 | 1.86      | 2.98    | 0.972 |
| OLS    | 5.22      | 29.98    | 0.701 | 8.37      | 23.41    | 0.728 | 3.22      | 3.63    | 0.976 |

IS-O, identification by use of self-oscillations; OLS, ordinary least-squares; DOF, degree of freedom.

Figure 9. Result of an identification by use of self-oscillations (IS-O) experiment applied on (a) yaw, (b) surge and (c) sway oscillations. [Colour figure can be viewed at wileyonlinelibrary.com]

the IS-O method are shown in blue. These results should give a clearer and more intuitive picture of the similarity between the IS-O and OLS obtained models.

Comment (on time responses of IS-O and OLS models)

Time responses shown in Figure 9 give an intuitive picture of the quality of the obtained models. Given the high noise in surge and sway speed measurements, the IS-O obtained models are of high quality.
Figure 10. Difference between the $R^2$ of identification by use of self-oscillations and ordinary least-squares models. [Colour figure can be viewed at wileyonlinelibrary.com]

The data sets for surge, sway and yaw presented in Figure 9 are used for validation of the IS-O models. The OLS identified model is used as a reference fit. The used model is the same as for IS-O. The OLS identification was performed directly on the IS-O validation data sets; thus, it should represent a high quality fit for that data set. In order to quantify the difference of OLS and IS-O, we observe the differences in the coefficient of determination ($R^2$) between the OLS and IS-O obtained.
models. Figure 10 shows the difference of $R^2$ for each IS-O obtained model relative to the reference OLS model.

Comment (on $R^2$ differences between the IS-O and OLS models)
Figure 10 clearly quantifies the differences between the models obtained using the presented IS-O method and the OLS approach. While for surge DoF, $R^2$ obtained with the IS-O model is never higher than 18% comparing with the OLS model, for sway DoF, this difference never exceeds 8%. Overall, the nonlinear model accounts only for about 70% of the variance, and in case of IS-O, surge identification is 60% on average. The rest can be attributed not only to noisy measurement but also to potential coupling, which is neglected in the model. In the case of yaw DoF, maximum difference is 4%. The model fits the existing data quite well with a high 97%.

Comment (on overall quality of IS-O models)
All in all, the presented analysis of results proves that the IS-O obtained models are comparable with OLS models. If we take into account the simplicity and time parsimony of the IS-O method, the conclusion is that it is highly applicable for full-scale identification of controllable DoFs of marine vessels in field conditions.

5. CONCLUSION

This paper focused on practical aspects of identifying full-scale models of overactuated surface marine vehicles. We demonstrated a practical approach of multiple thruster mapping on the example of an autonomous surface vehicle PlaDyPos. In addition to that, we showed how daisy-chained inspired inverse allocation approach can be applied to accomplish simultaneous omnidirectional motion. This approach, as shown on a real example, is of most value when one DoF is controlled (e.g. heading), while manual inputs that would normally saturate actuators are applied in other DoFs (e.g. surge and sway).

After the propulsion-level identification has been conducted, we focused on identification of dynamic model parameters by using self-oscillations. In previous work, we have demonstrated that (i) IS–O can be used for both linear and nonlinear model identification; (ii) IS-O provides explicit formulae for calculating unknown model parameters; and (iii) IS-O is time-parsimonious, which makes it practical for field application. In this paper, we came to the following conclusions regarding the IS-O method application:

- While the procedure for identifying yaw DoF using compass measurements has been described before, we provided a procedure for using the same methodology for identifying surge and sway DoF from oscillations obtained on directly integrated DVL measurements. These measurements are much smoother compared with raw DVL measurements and hence allow for determining precise parameters (magnitude and frequency) of obtained self-oscillations;
- A limited, small area is required to perform IS-O experiments, in comparison with classical identification methods where, due to the requirement on the persistent excitation of the input signal, a much larger area may be required to obtain a satisfactory model;
- Experiments have shown that the obtained model parameters are consistent regardless of experiment parameters, that is, output and width of relay with hysteresis. Inertia parameters in surge and sway DoF are identified with standard deviation of around 12%, while in yaw case, the deviation is around 4%. Identified drag parameters have a deviation of about 10%, while in the yaw model, it is about 23%;
- The IS–O obtained results are comparable with those obtained using OLS identification ($R^2$ for IS-O identified surge model is never higher than 18% for surge, 8% for sway and 4% for yaw model).

Taking all into account, we conclude that the proposed IS-O method is highly applicable for quick and reliable identification of marine vehicle parameters in real-life conditions.
6. NOMENCLATURE USED IN THE PAPER

| Term | Description |
|------|-------------|
| $\alpha_v$ | total single DoF inertia |
| $B$ | allocation matrix |
| $\beta(v)$ | general single DoF drag |
| $\beta_v$ | linear drag parameter for single DoF |
| $\beta_{v\nu}$ | nonlinear drag parameter for single DoF |
| $C(v)$ | rigid body and added Coriolis and centripetal matrix |
| $D(v)$ | total hydrodynamic damping matrix |
| $\Delta$ | constant disturbance |
| $F$ | vector containing forces $F_i$ exerted by each thruster |
| $F_i$ | force or moment generated by a single, $i$-th actuator |
| $\Phi(F)$ | generalized allocation map |
| $\eta$ | six element vector of positions and orientations of the vessel |
| $g(\eta)$ | vector of restoring forces |
| $h(n)$ | nonlinear actuator mapping |
| $M$ | rigid body and added mass matrix |
| $n_i$ | input of a single, $i$-th, actuator |
| $v$ | six-element vector of linear and rotational velocities of the vessel |
| $\tau$ | six-element vector of excitation forces and moments acting on the vessel |
| $\tau_E$ | vector of environmental forces and moments |
| $u$ | surge speed |
| $U_n$ | nominal battery voltage |
| $U_s$ | battery supply voltage |
| $u^\circ$ | integral of surge speed |
| $v$ | sway speed |
| $v^\circ$ | integral of sway speed |
| $C$ | relay output value |
| $f(\cdot)$ | general nonlinear process |
| $F(x)$ | nonlinear function describing the nonlinear element |
| $\omega$ | frequency of self oscillations |
| $p$ | the differential operator |
| $P_N$, $Q_N$ | describing function parameters |
| $T_H$, $T_L$ | duration of relay high and low output in one period |
| $x_0$ | bias in self-oscillations |
| $x_a$ | half the hysteresis width |
| $X_m$ | magnitude of self-oscillations |
| $x(t)$ | monoharmonic input to the nonlinear element |
| $Y_0$ | Fourier coefficients of the output of the nonlinear element |
| $y_N$ | output of the nonlinear element |

ACKNOWLEDGEMENTS

The authors would like to thank Nikola Stilinović and Milan Marković for their support during the trials. Special thanks goes to the Croatian Navy who provided the logistic support.

This work is supported by the European Commission under the FP7–ICT project ‘CADDY – Cognitive Autonomous Diving Buddy’ Grant Agreement No. 611373, and under the FP7 project ‘EUROFLEETS2 – New operational steps towards an alliance of European research fleets’ Grant Agreement No. 312762.
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