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DP Innovation

Automatic Tuning of a DP Vessel

John A. Leavitt, Benjamin I. Triplett, Alan C. Herold

L-3 Communications Dynamic Positioning and Control Systems (San Diego, USA) Secto 7G Systems (Seattle, USA), SAIC (Lynnwood, USA)

Abstract

Parameter estimation methods are applied to the mathematical model of DP control system. This work is based on a previously published paper, introducing more parameters to the formulation and focusing on automating the DP tuning process. The proposed methods are tested on a full scale vessel.

Introduction

To achieve optimum performance, a dynamic positioning (DP) system must have an accurate mathematical model of the vessel that it controls. In practice, vessel and hardware specifications provided by shipbuilders and vendors are sometimes inaccurate, incorrect, or absent. Such is often the case with parameters that are difficult to estimate without trialing the vessel in a real marine environment. For these reasons it is usually desirable to identify some of the system parameters at the time of commissioning. Some of these parameters include: maximum thrust ratings for actuators, rudder lift and drag coefficients, and water current drag models.

Because vessel commissioning can be lengthy and expensive, the system identification procedure should be concise and straightforward, and be readily carried out by service personnel who do not possess special expertise in control systems or system identification theories. The methods presented in this work, which build on an extended Kalman filter (EKF) approach ([1]), have been developed with these objectives in mind. Two alternatives to EKF, namely the unscented Kalman filter (UKF) and a least squares method, are explored. Because the estimation formulation of [1] covers only some of the most important parameters required to tune a DP system, new estimates are added to the formulation. These include a number of parameters for main propellers that are not always known with sufficient accuracy, namely a reverse efficiency factor, an exponential value used to convert propeller pitch to thrust, a zero-thrust pitch offset, and the effective propeller separation. Estimation of the center of gravity of the vessel is also added to the formulation.

While it is assumed that the identification process is carried out in the presence of negligible wind and wave disturbances, current sensors are not always available on a vessel. Hence, the test administrator is not generally aware if current disturbances are negligible. To allow for system identification in the presence of unknown currents, the water current speed and direction are explicitly estimated in the formulation. The identification procedure is then carried out while the vessel is subject to closed-loop position and heading control. The closed-loop nature of the approach lends itself for full automation of the DP software tuning process.

Low Speed Vessel Model

The mathematical model of a vessel that moves at low speeds (about 2 knots or lower) is taken from [2] and is also seen in [1]. This model's equations of motion of can be summarized in matrix form as:

$$M\dot{\nu} + C(\nu)\nu + D(\nu - \nu_c) = \tau + \omega \tag{1}$$

where $\nu = [u, v, r]^T$ is the velocity of the vessel in the body-fixed frame. The velocity of the vessel in an inertial reference frame (e.g. Northings/Eastings) can be written:

$$\dot{\eta} = \begin{bmatrix} \dot{n} \\ \dot{e} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} u \\ v \\ r \end{bmatrix}. \tag{2}$$

Note that only surge, sway, and yaw velocities are included in ν, as it is assumed that pitch, roll, and heave dynamics are neglible. The vector $\nu_c = [u_c, v_c, r_c]^T$ is the water current velocity vector, such that $\nu - \nu_c$ is an expression of the speed through water of the vessel in the body frame. In this work we assume that $r_c = 0$, meaning that any water current present can be modeled as a uniform vector field. Furthermore, we will assume that water current does not vary with time. The vector $\tau = \left[F_x, F_y, M_\psi\right]^T$ contains the surge and sway-axis control forces, as well as the yaw-axis control moment. The process noise vector ω represents the combined effect of modeling errors and any environmental disturbances not accounted for, such as wind and wave forces.

The matrices *M*, *C*, and *D* are written:

$$M = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix}, \quad C(\nu) = \begin{bmatrix} 0 & 0 & -m_{22}v - m_{23}r \\ 0 & 0 & m_{11}u \\ m_{22}v + m_{23}r & -m_{11}u & 0 \end{bmatrix}, \quad D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & d_{23} \\ 0 & d_{32} & d_{33} \end{bmatrix}. \tag{3}$$

Using guidelines from [2], the five non-zero elements of *M* were approximated from the actual mass *m* of the vessel and the concept of *added mass*. See [2] for further details. The five non-zero elements of *D* are considered to be unknowns to be estimated.

The thrusting force *T* generated by a rotating propeller is approximated by the equation:

$$T = \begin{cases} T_{\max} \left|\dfrac{\omega}{\omega_{\max}}\right|^{k_1} \left|\dfrac{p - p_0}{\Delta p_{\max}}\right|^{k_2} & \omega(p - p_0) \geq 0 \\ -T_{\max} k_3 \left|\dfrac{\omega}{\omega_{\max}}\right|^{k_1} \left|\dfrac{p - p_0}{\Delta p_{\max}}\right|^{k_2} & \omega(p - p_0) < 0 \end{cases} \tag{4}$$

where $-\omega_{\max} \leq \omega \leq \omega_{\max}$ and $-\Delta p_{\max} \leq (p - p_0) \leq \Delta p_{\max}$. Here ω and p are the rotational velocity and pitch (blade angle) of the propeller, respectively. The exponent values k_1 and k_2 are typically taken to be 2.0 and 1.5, respectively. The reverse efficiency factor k_3 satisfies $0 < k_3 \leq 1$, while T_{max}, ω_{max}, and Δp_{max} are positive real numbers representing maximum achievable values. Finally, p_0 is the pitch value at which zero thrust is achieved.

If a rudder is used in combination with the propeller, the lift and drag forces, *L* and *D,* are often modeled using nonlinear functions that take *T* and the rudder angle δ as inputs (for example, [3]). The net forces exerted by a propeller-rudder pair labeled *i* can then be written:

$$\begin{aligned} F_{x,i} &= T_i - D_i \\ F_{y,i} &= L_i . \end{aligned} \tag{5}$$

Azimuthing thrusters, having an orientation α_i defined relative to the forward direction (clockwise = positive), exert forces according to:

$$F_{x,i} = T_i \cos \alpha_i$$

$$F_{y,i} = T_i \sin\alpha_i . \tag{6}$$

In the case of a tunnel thruster, we have $\alpha_i = \pi$, resulting in $F_{x,i} = T_i$, $F_{y,i} = 0$. The control vector τ seen in equation 1 is then calculated as:

$$\tau = \left[F_x, F_y, M_q\right]^T = \begin{bmatrix} \sum_i F_{x,i} \\ \sum_i F_{y,i} \\ \sum_i F_{y,i} x_{cg,i} - F_{x,i} y_{cg,i} \end{bmatrix}, \tag{7}$$

where $x_{cg,i} \equiv x_i - x_{cg}$ and $y_{cg,i} \equiv y_i - y_{cg}$ are the surge and sway-axis distances of the i^{th} thrusting device to the center of gravity of the vessel, respectively.

Formulation of the Parameter Estimation Problem

Parameter Selection

The first step in formulating the parameter estimation problem is to decide which parameters are known with sufficient accuracy, and which parameters are considered to be unknown. The following table is a summary of the parameters that are considered in this work to be the unknown parameters of a typical supply vessel:

Parameter Descriptions	*Symbols*	*Estimation Phase*
damping matrix coefficient, surge	d_{11}	I
damping matrix coefficients, sway and yaw	d_{22}, d_{23}, d_{32}, d_{33}	II
water current velocity, N-E components	$\dot{n}_c$, $\dot{e}_c$	I, II, III
pitch-to-thrust exponent, main propellers only	k_2	I
reverse factor, main propellers only	k_3	I
zero-force pitch, main propellers only	p_0	I
main propeller distance to centerline	$y_{cg,i}$	III
maximum thrust ratings, tunnel and azimuthing thrusters only	$T_{i,\ max}$	II
rudder coefficients	[model dependent]	III
center of gravity, surge-axis component (optional)	x_{cg}	II

Table 1. Unknown parameters of a typical supply vessel with variable pitch propellers.

Here the main propellers of a workboat are treated differently than tunnel and azimuthing thrusters. One reason is that they typically have a much higher thrust rating than is required for low-speed motion control. As a result, a typical workboat's main propellers will operate at relatively low thrust levels (for example, the 5% range). This makes the DP system sensitive to errors in the "pitch to thrust" exponent,

k_2, as well as the zero-force pitch, p_0. Another important distinction is that main propellers operate inefficiently in reverse compared to most other actuators. This is because main propellers are typically designed for forward thrust, and because wash interacts with the vessel's hull when the propellers run in reverse. A tunnel thruster, on the other hand, typically has the same hull interaction regardless of which direction its wash is directed. Azimuthing thrusters usually extend down below the hull, and in this case it is reasonable to assume that any hull interaction is negligible. The final distinction is that main propellers often have much larger diameters than other thrusters. As a result, it may not be sufficient to assume that the thrust vector generated acts at the propeller's center. For this reason, we consider a main propeller that is the vessel's i^{th} thruster to have an unknown distance, $y_{cg,i}$, to the centerline.

While the thrust ratings of main propellers can be verified experimentally at the time of commissioning using a "bollard pull" type test, the maximum thrust ratings of other thrusters present are not usually known with much accuracy. This is due in part to the fact that certain settings, such as the maximum pitch controllable by the DP system, are sometimes adjusted by the vendor at the time of commissioning. Hence, the tunnel and azimuthing thrusters of a workboat vessel are considered to have unknown thrust ratings $T_{max,i}$.

Because the experimental identification of rudder model parameters has not been sufficiently explored at the time of this printing, the topic will have to be treated in a future publication. All tests mentioned herein have been performed with the rudders fixed at their center (neutral) positions.

The last parameter in Table 1 is considered optional. Due to symmetry, it is usually the case that $y_{cg} = 0$. Furthermore, the location of the center of gravity along the ship's centerline, x_{cg}, is often provided by the ship builder with reasonable accuracy.

Maneuver selection

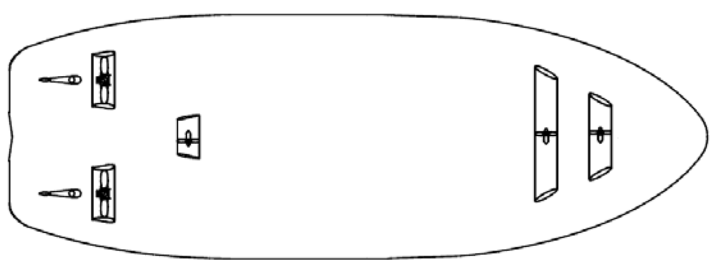

Fig. 1. Thruster configuration a typical DP Class 2 supply vessel.

The strategy from this point is to determine a set of maneuvers (or actuator commands in the case of open-loop control) that will persistently excite the vessel and actuator dynamics, such that they can be observed by an estimation algorithm. In general, the selection of these maneuvers is independent of the estimation algorithm itself. In order to maintain a relatively short estimation procedure, and to ensure that our assumption about constant water currents is valid, we have limited the duration of each recorded maneuver to 20 minutes.

For the workboat configuration seen in Figure 1, three sets of maneuvers have been tested. As seen in [1], these maneuvers define three sequential estimation phases, in which the estimated parameters from previous phases (excluding water current) are *frozen* and considered known in the current phase. Phases I, II, and III are termed the *decoupled surge*, *coupled sway and yaw*, and *azimuthing* phases, respectively. The last column of Table 1 lists each parameter's corresponding phase.

Simulations using the vessel and actuator models of the previous section suggest that simple sinusoidal oscillations in the commanded surge-axis position of the vessel around a fixed point, using tunnel thrusters to maintain heading and sway position, are sufficient for the decoupled surge phase. Two such motions were simulated at reciprocal headings, with the period and amplitude of the oscillations chosen such that the peak velocity achieved was less than two knots, and such that the peak thrust levels achieved by the main propellers remained below 10%. During the maneuvers, each axis (surge, sway, and yaw) was subject to closed-loop control. Closed-loop control eliminates the chance that the vessel will drift into varying current regions and thus invalidate our assumptions about constant water currents. It also helps us to obtain motions that are both low-speed and performed at reciprocal headings. The latter requirement is needed to be able to discern thruster offsets from environmental disturbances.

In the coupled sway and yaw phase, simulations have indicated that simultaneous sinusoidal oscillations in sway and yaw (heading) may be needed to identify the center of gravity of the vessel, as well as the coefficients, d_{23} and d_{32}, of the damping matrix that represent coupling between sway and yaw motions. Two such motions, starting at reciprocal headings, seem to be sufficient. Good results have not been obtained when pure sway and pure yaw motions have been performed separately.

In the final phase, the only parameters that remain to be identified are the main propeller separation, and those pertaining to the rudder model. Knowledge of the separation of the main propellers is not required in the previous phases if the main propellers are always issued identical commands. Also, preliminary simulations have indicated that pure sway motions may be sufficient for this phase.

Algorithm Selection

An extended Kalman Filter (EKF) was used in [1] to estimate various unknown parameters of a supply vessel. Recursive estimation algorithms, including EKF, are useful in online parameter estimation problems (where processing time is at a premium) because only data from the current sample is processed in a given cycle. Furthermore, recursive algorithms can estimate the values of slowly varying parameters in real time. As implied in [1], an online estimation approach is probably not suitable for identifying the mathematical model of a surface vessel. This is primarily because the estimator does not have access to enough data to identify all the required unknowns. For example, forces due to water currents may be difficult to distinguish from main propeller feedback offsets during surge maneuvers performed at a fixed heading. The parallel offline implementation of the EKF proposed in [1] is a solution to this problem. The estimator runs recursively through multiple streams of recorded data in a parallel fashion, and was reportedly effective on a full-scale vessel.

UNSCENTED KALMAN FILTER

Recently, the unscented Kalman filter (UKF) has been shown to have certain advantages over EKF in nonlinear estimation problems (e.g., [4] and [5]). These advantages include increased accuracy, stability, and ease of implementation. Consequently, the authors have formulated the parallel offline estimator of [1] as a UKF (refer to [6] for a complete description of the UKF). Simulations with the UKF have yielded accurate estimates, but when applied to the full scale experiments described later, the UKF proved difficult to work with. One problem seen in both simulated and real data is long convergence times, particularly in Phase II where many parameters are estimated. Because the recorded data streams cannot be arbitrarily long, it has been necessary to run the algorithm multiple times on the same set of data to achieve convergence. In a real environment subject to unmodeled dynamics and real noise, rerunning the same data set multiple times was ineffective. One possible problem is that some parameters in the formulation, like the pitch-to-thrust exponent k_2, only have meaning within a certain range of values. It is hoped that applying bounds to the estimates, using a method such as described in [5], will help to achieve good results in the future.

LEAST SQUARES METHOD

In offline applications, least squares methods are an attractive alternative to Kalman filtering methods because bounds are easily applied to the estimates, guaranteeing a feasible solution, and because little or no tuning of the algorithm is required. Furthermore, unlike a recursive formulation, they have access to all of the recorded data at each iteration. The least squares approach used in this research is similar to the multiple shooting method described in [7], and applied to parameter estimation in such works as [8] and [9]. The formulation is as follows:

Consider the function *f*, that takes vector inputs *x(t), u(t)*, and *p*, such that

$$\dot{x}(t) = f(x(t), u(t), p), \qquad x(t) \equiv [\eta(t)^T,\ \nu(t)^T]^T, \tag{8}$$

where *u(t)* is a vector of control inputs, and *p* is a vector of constant parameters to be estimated. The measured position and control vectors $\hat{\eta}_k$ and $\hat{u}_k$, sampled periodically, are defined as $\hat{\eta}_k \equiv \eta(t_0 + k\Delta t) + \nu_k$, and $\hat{u}_k \equiv u(t_0 + k\Delta t) + \mu_k$, where ν_k and μ_k are measurement noise vectors consisting of normally distributed random numbers having zero mean. The sample time Δt used here is 0.22 seconds. Curve fitting techniques are applied to the measured position data to obtain estimates of the full state trajectory, $\tilde{x}_k$. The model trajectory, x_k, is defined as:

$$x_k = \begin{cases} \tilde{x}_k, & k \in \{0,\ N,\ 2N, \ldots (m-1)N\} \\ f(x_{k-1}, \hat{u}_{k-1}, p) \cdot \Delta t + x_{k-1}, & k \notin \{0,\ N,\ 2N, \ldots (m-1)N\} \end{cases} \tag{9}$$

where *m* is an integer representing the number of times in a given run that the model trajectory is reinitialized to the estimated value, and *N* is an integer defined such that the total number of samples in the data set is *mN*, and $0 \le k < mN$.

The objective is to find a set of parameters, *p*, that in some way minimizes the differences (or *residuals*) between the measured position vectors and the position vectors of the model trajectory at each sampling instant. To achieve this objective the problem is formulated as:

$$\min_p \sum_{i=0}^{Nm} e_i^{\,T} W e_i, \tag{10}$$

where $e_i \equiv \hat{\eta}_i - diag([1\ 1\ 1\ 0\ 0\ 0]) \cdot x_i$, and subject to box constraints $p_{\min} \le p \le p_{\max}$. Here *W* is defined simply as $W = diag([1\ 1\ \frac{180}{\pi}])$, such that a 1 degree residual and a 1 meter residual have equal weighting.

In obtaining a solution to this optimization problem, MATLAB's interior point algorithm from the function *fmincon* was found to be superior to MATLAB's large-scale nonlinear least squares algorithm. The former is reportedly taken from [10], [11], and [12], and the latter is reportedly a subspace trust-region method based on the interior-reflective Newton method described in [11] and [13].

Full Scale Experiments

Decoupled surge and coupled surge/sway maneuvers were performed on a supply vessel owned and operated by Hornbeck Offshore Services, Inc. The thruster configuration of this vessel, shown (not to scale) in Figure 1, consists of two tunnel thrusters in the bow, a tunnel thruster in the stern, and the usual pair of mains and rudders. The thrusters and main propellers were configured to operate with fixed shaft velocities, and are labeled T1 through T5, corresponding to the forward bow tunnel, aft bow tunnel, stern tunnel, port main and starboard main propellers, respectively. The decoupled surge tests were performed with nearly zero wind levels, and the remaining tests were performed in the presence of 5-12 knot winds (see Figure 6). In these cases, the vessel was oriented approximately parallel to the winds to minimize wind forces. T1, the forward bow thruster, was disabled to simplify the estimation problem (another option would have been to assume that each bow thruster has an identical thrust rating). The recorded position and control feedbacks are seen in Figures 2-5. Table 2 contains the estimates obtained from the least squares method. Where applicable, the parameters have been normalized according to the *Bis-system* normalization scheme in [14].

Parameter	*Estimated Value*	*Expected Value*
d_{11} (normalized)	0.0054	0.0358 (from [1])
d_{22} (normalized)	0.0798	0.1183 (from [1])
d_{23} (normalized)	0.0150	-0.0124 (from [1])
d_{32} (normalized)	-0.0101	-0.0041 (from [1])
d_{33} (normalized)	0.0117	0.03080 (from [1])
k_2	1.145	1.5
k_3	0.45	$0.4 < k_3 < 0.7$
p_0	-8%	observed to be < 0
x_{cg} (normalized)	0.0083 aft of nominal	0
$T_{max,2}$ (normalized)	0.001387	0.001663
$T_{max,3}$ (normalized)	0.001664	0.001663

Table 2. Estimated parameters (using least squares method) of a full-scale supply vessel with variable pitch propellers.

The first five estimates, representing the normalized D matrix (labeled D″ in [1]) coefficients, are in rough agreement with the values seen in [1] and listed in the “Expected Value” column of the table, with the exception that d_{11} appears to be too low. The pitch-to-thrust value (k_2) is quite low compared to the expected value. Its proximity to unity indicates that the hardware providing the main propeller feedback signals to the DP system may be outputting calculated thrust instead of measured pitch. The pitch offset is in agreement with joystick (manual) testing, which indicated a negative value. The remaining estimates in the table are in agreement with expected values.

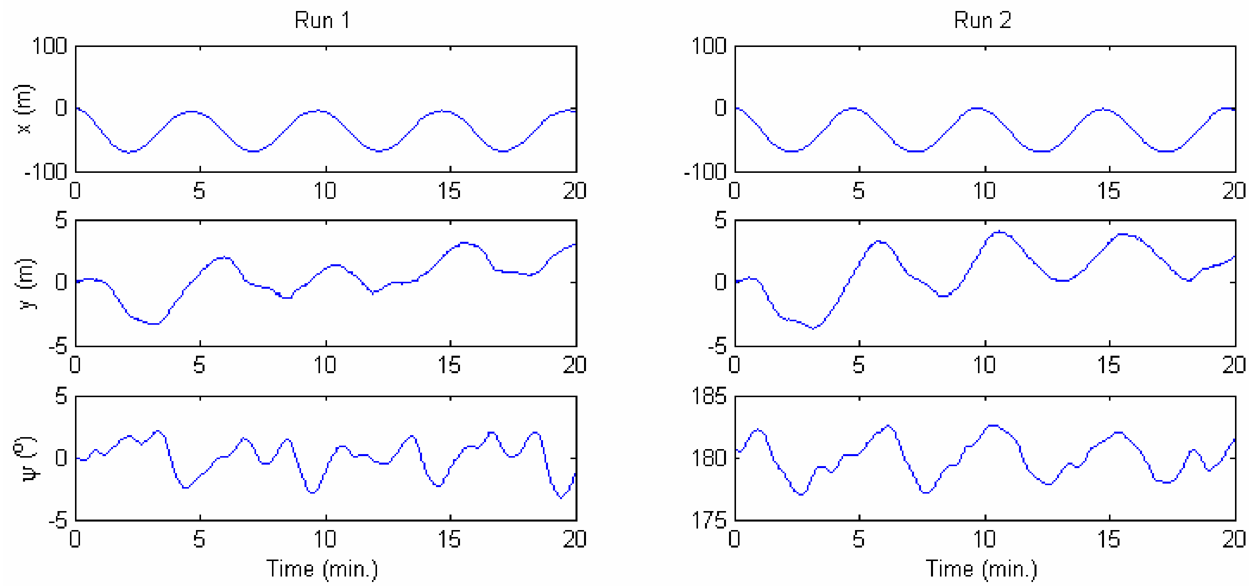

Fig. 2. Decoupled surge tests on the full scale vessel: position and heading (ψ) data.

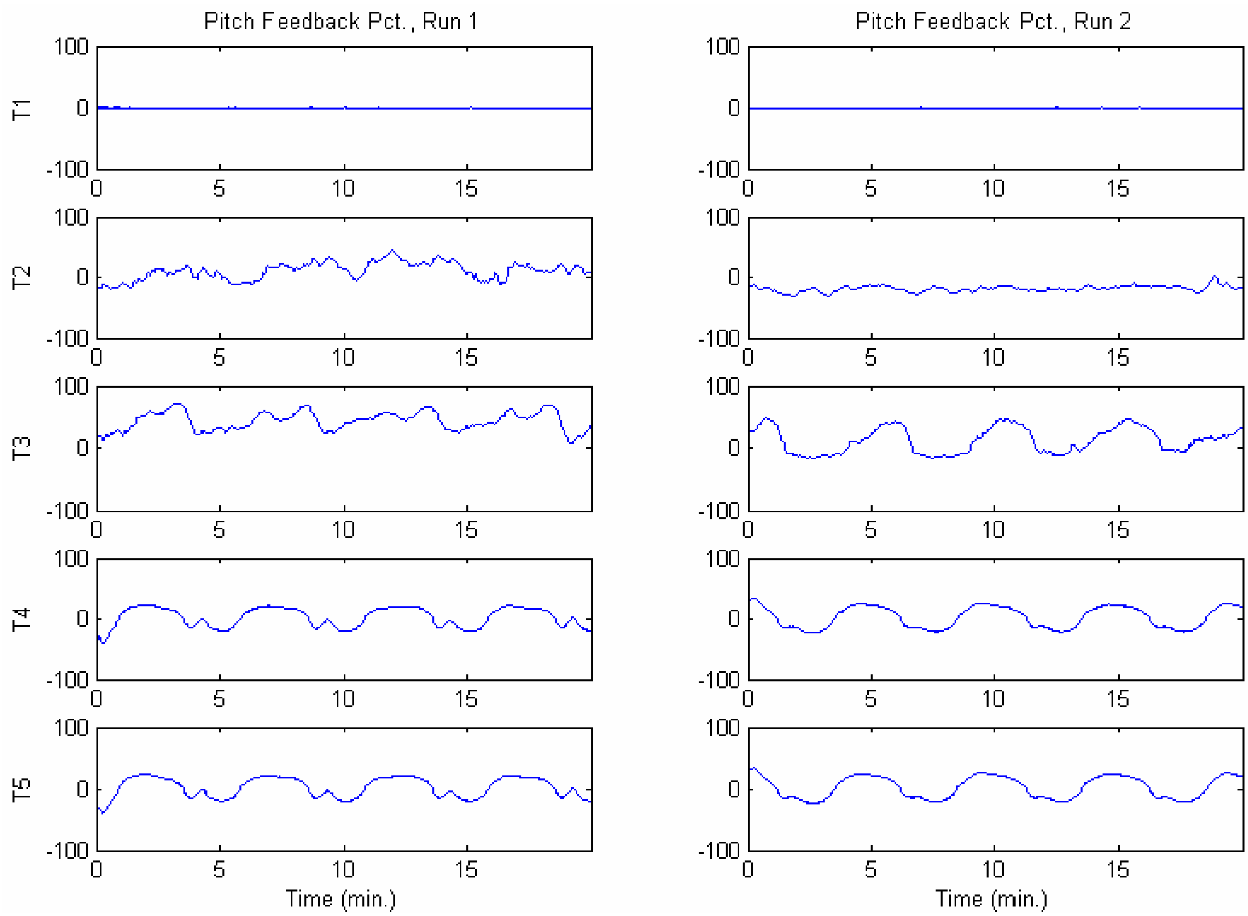

Fig. 3. Decoupled surge tests on the full scale vessel: pitch feedback for each of the five propellers, labeled T1-T5.

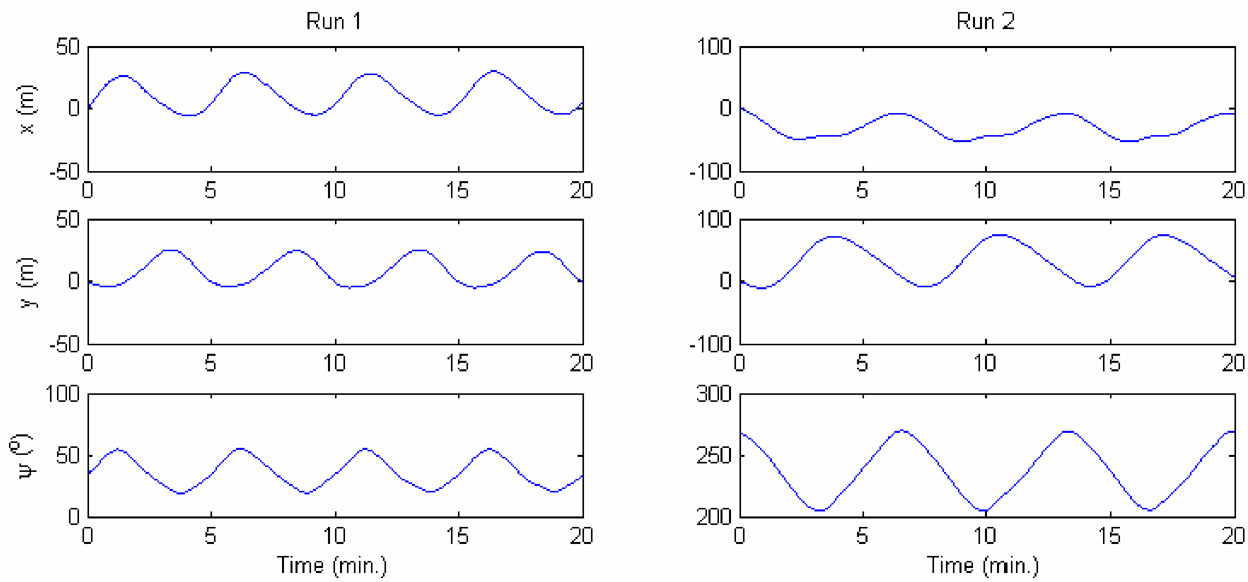

Fig. 4. Coupled surge/sway tests on the full scale vessel: position and heading (ψ) data.

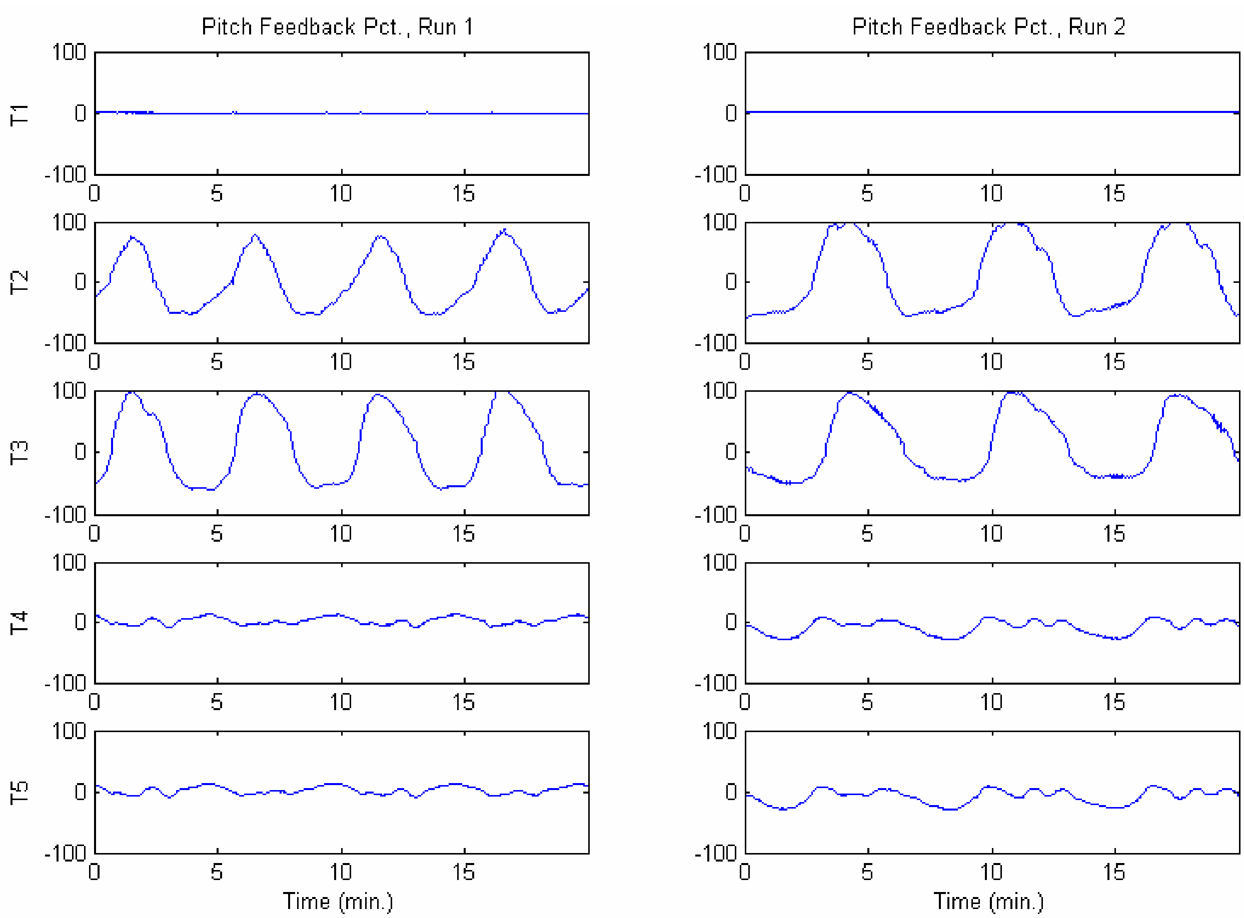

Fig. 5. Coupled surge/sway tests on the full scale vessel: pitch feedback for each of the five propellers, labeled T1-T5.

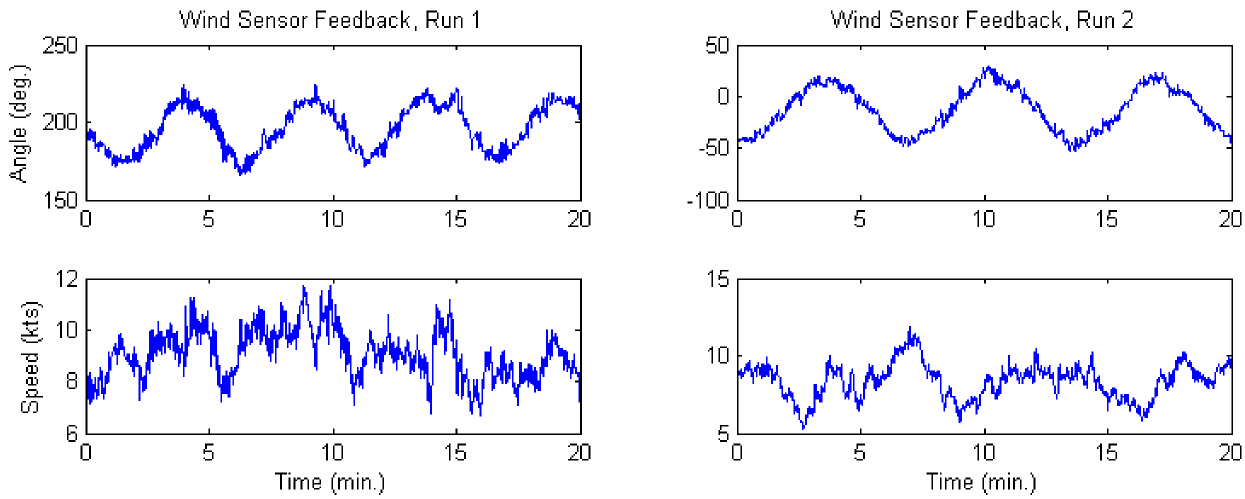

Fig. 6. Coupled surge/sway tests on the full scale vessel: wind sensor feedback (relative to the body frame).

Conclusions

An existing identification scheme is expanded to apply more generally to offshore supply vessels. Various new parameters are added to the formulation, and two estimation algorithms are explored as an alternative to EKF, namely the unscented Kalman filter (UKF) and a least squares minimization method similar to multiple shooting. Vessel maneuvers used in the system identification process are performed under closed loop control, potentially allowing for fully automated tuning of the DP System.

Much of the identification procedure is tested on a full-scale supply vessel, and the least squares method is found to obtain reasonable parameter estimates, with the possible exception of the surge-axis water damping coefficient. UKF is found to be difficult to work with, but further research efforts are needed before conclusions can be drawn regarding its usefulness in this application.

Acknowledgements

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About the Authors

John A. Leavitt is a Guidance, Navigation and Control Engineer at L-3 Communications, Dynamic Positioning and Control Systems, in San Diego, CA. He received his PhD in Mechanical and Aerospace Engineering at the University of California, Irvine, in 2006. At UCI, John worked on a number of gas powered (pneumatic) control systems, including an under-actuated hopping robot which he designed and built. John was an ARCS Foundation scholar, Orange County Chapter, among other honors. His research interests include motion control of robots and vehicles, system identification, and optimization theories.

Benjamin I. Triplett received his B.A.Sc. in Engineering Physics from The University of British Columbia in 2000, where he focused on mechanical design. Ben was a member of the original UBC solar car team and he founded the UBC SAE Aero Design Open Class team. After receiving his M.A.Sc. from UBC in Mechanical Engineering in 2002, Ben began his post-Master’s work at the University of Washington in the department of Aeronautics and Astronautics. Ben’s research at the UW focused on robotics, embedded systems, coordinated control, and cooperative target tracking, with an emphasis on advanced estimation algorithms for nonlinear systems. Ben received the Hertzberg Research Award in 2004 and graduated with his Ph.D. in June of 2008.

Alan C. Herold is a 1970 graduate of the University of Washington, holding a Master's degree in Aeronautics and Astronautics with an emphasis on control systems. He is presently a Principal Systems Engineer with SAIC in Lynwood, Washington and has 32 years of direct experience with all aspects of marketing, program management, specification, design, coding, deployment, and verification of complex commercial and government marine instrumentation and control systems. Commercial assignments have include development and commissioning of a large number of custom dynamic positioning systems for support vessels, deep ocean drilling rigs, dive support, research, pipe and cable-lay, ice-breaking, buoy tending, and ROV operations. Recent military projects have included the development of a major underwater range to provide acoustic tracking, and electric, magnetic and acoustic signature measurement, a conceptual design for a system to deploy and track concentrations of underwater plumes, and distributed simulations for a multitude of autonomous underwater vehicles.