Autotuning Aspects for Dynamic Positioning Systems

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Abstract: This paper considers aspects related to the problem of automatic tuning (autotuning) of dynamic positioning (DP) controllers for marine surface vessels. Autotuning involves automatic adjustment of controller parameters for shifting vessel operational conditions (VOCs), which encompass changing vessel dynamics and different operational tasks. A controller with fixed gains cannot behave equally well for all VOCs and autotuning can thus be very valuable in practice, saving time for commissioning and improving operational robustness. In this work, we review some previous work and discuss fundamental concepts within the subject area. We also propose a novel performance index for station-keeping purposes and use this index together with an autotuning algorithm which employs data generated from the index. Finally, some simulation results concerning station keeping of an offshore supply vessel operating in challenging sea-state conditions are included.

1. INTRODUCTION

Dynamic positioning (DP) technology for marine surface vessels was primarily developed as a consequence of the move into deeper waters by the oil and gas industry during the 1960s. In this regard, the classification company DNV defines a dynamically positioned vessel as a free-floating vessel that maintains its position exclusively by the use of active thrusters. According to (Bray 2003), the drilling exploration vessel Eureka was the first to fulfill this requirement. Eureka was built in 1961 and fitted with a very basic analog control system using automatic electromechanical devices. The propulsion equipment consisted of two steerable thrusters, one fore and one aft, in addition to the main propulsion. Today, over 1000 DP-capable vessels are in operation around the world. Even though these vessels and their operational tasks vary greatly, they all depend on making a profit for the shipowner by operating safely with high precision.

Starting out as basic analog systems, today’s DP control systems are digital, computer-based systems with sophisticated functions that help improve safety, precision, and profitability, see Figure 1. With the rapid development within computer technology and the accompanying price reduction in storage and processing power, more sophisticated functions that help improve these metrics even further can be implemented in the future, including functionality for autotuning.

Today, the controller parameters of a DP system are typically tuned with respect to minimizing the deviation in position and heading (pose), and the tuning is typically carried out at a sea trial during the commissioning of the vessel. Sea trials are performed at design draught and for minimum environmental disturbances, and the controller parameters obtained from such tuning are necessarily not optimal for all types of operations and shifting conditions. For some vessel operational conditions (VOCs), a DP operator might experience that the controller uses unnecessarily large amounts of thruster force to keep position and heading, while in other situations the vessel might have problems achieving this objective at all. Different operations might also have different requirements for pose accuracy, which enables a reduction in thruster activity. Hence, the two conflicting objectives of operational accuracy and energy saving must be balanced.

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Even though a vessel is exposed to shifting VOCs, and even though different operations require different accuracy levels, the conditions and operations can be seen as static during a limited time window. It should thus be possible to find an ideal control parameter set for this period. Also, it is natural to assume that conditions similar to the current will reappear in the future. Hence, by storing experience from the current situation, e.g., a lookup table, the corresponding control parameters can be used for a similar future situation. This concept compares how a captain uses experience when operating a vessel in different operational conditions. However, most conventional DP systems on the market today use only present values and not historical data when optimizing the controller. Control gain adjustments to shifting conditions are often solved manually by a low, medium, or high gain selection (Bray 2003). A potential thus exists to improve current schemes by introducing autotuning methods that rely on both present and historical data when deciding the controller gains that must be applied for a given VOC.

1.1 Previous Work

Little material exists on autotuning of DP controllers, and most of the work concerns adaptive estimation of model parameters. However, some relevant literature is reported in the following. In (Selkkiinaho 1993), different tuning methods based on model identification are tested. To separate out wave-induced forces showed to be difficult, and the only method showing some success was based on offline optimization. Data used in the optimization was real-time data logged at a sea trial. In (Lee et al. 2001), a neural network predictive controller is proposed, using neural networks to estimate the unknown nonlinear terms in a 3 degree of freedom (DOF) vessel model, and combining this estimation with an optimal controller to form a predictive controller. In (Fang et al. 2004), a global output feedback controller is presented, having an adaptive approach where neither the ship parameters nor the velocity must be known. A drawback is that the global asymptotic position tracking stability proof only holds in a disturbance-free case. In (Martin and Katebi 2005), different MIMO PID tuning methods are discussed and tested for DP controllers, but none of the discussed tuning methods concern autotuning. However, it is suggested that the proposed tuning methods are possible to automate. In (Do 2007), a method to design a robust adaptive output feedback controller for surface vessels is considered. The controller does not need velocity measurements due to the introduction of a novel adaptive observer working both as an estimator and a filter. In (Nguyen et al. 2007), a hybrid controller is proposed with switching between different controllers for different sea-state levels. The controllers are pretuned and the switching is then automated. The different wave states are detected from the estimation of the wave disturbances in an adaptive observer.

1.2 Contribution

This paper is based on (Alme 2008) and discusses some fundamental aspects of autotuning for DP controllers. A novel performance index for station-keeping purposes is suggested together with an autotuning algorithm that uses data generated from this performance index.

2. PERFORMANCE INDEX FOR STATION KEEPING

Autotuning is a process whereby the controller parameters are somehow automatically adjusted. This automatic adjustment can be done discretely by demand of an operator or be a continuous process. Roughly speaking, an autotuning procedure can be divided into an identification phase and a controller design phase involving parameter calculations. For the identification phase, the process must be brought under some kind of excitation, which is normally carried out by applying a step or one or several periodic signals to the input of the process. Another method is the frequency-response method, which is based on finding the critical frequency and the critical gain of the process through oscillations. Other phrases used for autotuning controllers include self-tuning controllers and adaptive controllers.

The use of so-called intelligent methods for automatic tuning of controllers has attracted much interest during the last decade. A lot of methods employ so-called genetic algorithms (GAs), see, e.g., (Zuo 1995), (Lennon and Passino 1997), (McGookin et al. 2000), and (Salto 2005). Other examples of intelligent methods used for autotuning include fuzzy neural networks, reinforcement learning, and so-called immune algorithms. In (Shen 2001), a fuzzy neural network is used for tuning a PID controller; in (Wang et al. 2007) and (Sedighzadeh and Rezaazadeh 2008), adaptive PID controllers based on reinforcement learning are mentioned; and in (Dong and Cho 2004), an immune algorithm is used to tune a PID controller.

However, before choosing which method to use in an autotuning procedure, it is essential to define what constitutes good performance. Performance assessment then naturally necessitates a performance index.

2.1 Performance Assessment

When defining what represents good performance, considerations must be made about:

- **Reference values**: Regulating toward a constant setpoint, good performance can be to minimize the integral of the absolute (or squared) error. On the other hand, for a setpoint change, good performance can be to minimize settling time and at the same time minimize or be inside a limit for overshoot. Because the integral of the absolute (or squared) error might be low for a short settling time with large overshoot, this measure might not represent the best performance assessment. However, a combined performance metric might be a better choice.

- **Disturbances**: Often named disturbance rejection, the definition of good performance might in this case be regarded equivalent to a step change in the setpoint. The preferable solution is a fast response to the setpoint, with minimum or no overshoot.

- **Efficiency**: For a DP control system, efficient performance means that it shall keep or track the reference value with both a minimum amount of control effort and a low rate of change of this effort. The amount should be minimized to reduce the energy use, while the rate of change should be minimized to reduce wear and tear of the actuators.
• Actuator limits: For most control systems, there will also be saturation limits to the available actuators. Breaking these limits can render the system unstable.

To summarize, the definition of a performance index suitable for a controller can be seen as a function of the controller ability to follow the reference values, its response to load disturbances, its control effort efficiency, and its ability to handle actuator limitations. Another point is that a considerable use of control effort or a large rate of change in such efforts might not result in better setpoint-regulation or trajectory-tracking performance. Hence, it might be preferable to have a minor deviation in the position compared to the applied control effort. This aspect is especially relevant for DP operations in higher sea states, where it might be preferable to relax the accuracy in positioning against the effort of obtaining such accuracy.

Several definitions of performance indices can be found in the literature, and a good survey is given in (Jelali 2006). Traditional performance indices include minimum variance (MV), integral of absolute error (IAE), integral of squared error (ISE), integral of time-weighted absolute error (ITAE), and integral of time-weighted squared error (ITSE). However, few of the established performance indices take into consideration the associated control effort. The focus is on setpoint deviation or rejection against disturbances. Also, they do not give an operator of the system a clear picture of the performance.

A relevant performance index for DP operations must focus on the performance balance between setpoint deviation and control effort. Besides being useful for an autotuning algorithm, this index should also give an intuitive and straightforward picture of the performance to a DP operator.

**Performance Index for Autotuning** It is preferable that the performance index is continuous and that it can be directly related to the mathematical system model and the manipulated variables. Furthermore, it is preferable that the index represents a function which involves diminishing returns, i.e., referring to a situation where a smaller result is achieved for an increasing amount of effort. For a control system, the area involving diminishing returns will be a function of different controller parameters like the gains of a PID controller or the weights of an LQ controller.

**Performance Index for DP Operators** A performance index for a DP operator can function as a decision support tool, where valuable information includes how large the pose deviation has been for the last $t_m$ minutes; whether it is the average or peak pose deviation that is bad and how large the peaks are; whether it is possible to achieve better performance in pose (implicitly increasing the controller gains) or whether the actuators already are performing at their maximum; whether it is possible to reduce the control effort (implicitly reducing the controller gains) and still stay inside the pose limits; what and how much actually changes in the performance if the controller gains are changed (manually or by autotuning); which DOFs have the best and worst performances (according to the control effort and associated pose keeping). Based on such factors, the performance index should illustrate how large percentage of the last $t_m$ minutes the pose has been outside some mission-defined limits. Furthermore, it should illustrate the balance between pose and control effort.

A visual log of the change in performance can also be informative, see Figure 2. With such information, the DP operator can obtain a better understanding of how well the DP system performs. Such a system can also help him tune controller gains and possibly reduce the control effort, if possible slackening the evaluation limits for the DOF with the worst performance.

**Vessel Operational Conditions** Since marine vessels perform complex operations in shifting conditions, it can be useful to be able to quantify their operational conditions. According to (Perez et al. 2006), a vessel operational condition (VOC) can be defined as $VOC = (VUM, ENV, VC)$, where:

- $VUM$ refers to the vessel use mode, which describes the current task of the vessel, such as, e.g., drilling, pipe laying, etc.
- $ENV$ refers to the state of the environment, i.e., wind, wave and current conditions.
- $VC$ refers to the present condition of the vessel, spanning over the loading condition, vessel speed, available power, etc.

Since this paper mainly considers station-keeping operations, the velocity and vessel use-mode attribute will be constant and can be omitted from the definition. Also, the loading condition will be defined as a draught condition. According to (Fossen 2002), changes in water depth can also have an effect on the vessel performance, and represents an additional factor to consider. Hence, we define a VOC variable as $O(\delta, \varepsilon, \varpi)$, where $\delta$ represents draught, $\varepsilon$ represents the environmental conditions, and $\varpi$ represents the water depth, as is graphically illustrated in Figure 3.

![Performance log](image-url)

Fig. 2. Performance values for surge and sway forces as well as position deviation for different controller gains. A time window of $t_m = 5$ minutes is used to detect the performances for each tuning period. Red represents bad, yellow ok, and green good performance. The arrows indicate the change in performance.
Fig. 3. The vessel operational condition space.

2.2 Station-Keeping Performance Index

Based on the previous discussion, a performance index suited for station-keeping applications is proposed as a total index $J_T$, which is a function of how well the vessel keeps its setpoint in position and heading inside some predefined limits, as well as the required control effort for doing so. Hence, $J_T$ is a function of a position error index $J_p$, a heading error index $J_h$, and a control effort index $J_c$.

For a vessel performing station-keeping operations at sea, setpoint deviations in position will always occur due to disturbances from waves, wind and currents. The deviation will typically differ in surge and sway due to the vessel geometry, which suggests that its size must be related to a BODY-fixed reference frame. Consequently, the position index $J_p$ can be defined as ellipses in the BODY frame. Furthermore, 3 performance levels can be employed, where the inner level represents the minimum possible deviation for the considered VOC (highest accuracy), the mid level represents the nominal operational area (intermediate accuracy), and the outer level represents the maximum acceptable deviation for the VOC (lowest accuracy). These areas can also be seen as the green, yellow, and red operational sectors of Figure 4, respectively. Similarly, 3 performance levels can be defined for the heading error index $J_h$. Details about how the level limits can be chosen are found in (Alme 2008).

By using these limits, $J_p$ and $J_h$ can be calculated as a weighted sum of how long the vessel stays inside each level for a purposefully chosen time window of $t_w$, minutes. The calculations are made such that the indices are defined in a range from 0 to 100, i.e., $J_i \in [0, 100]$, $i \in \{p, h\}$, where 100 represents excellent performance and 0 constitutes poor performance. The weighting factors can be used to adjust the relative importance of each performance level, but excellent performance can only be obtained by staying inside the innermost level throughout the whole time window.

Control effort indices $J_c \in [0, 100]$, $j \in \{\text{surge, sway, yaw}\}$ are then calculated for each DOF to punish variations in the control effort. For these indices, 100 represents no variations, while 0 represents maximum variations.

Based on the position error, heading error, and control effort indices, performance indices can now be calculated for each DOF as, e.g.,

$$J_{T,\text{surge}} = \lambda_{\text{surge}} J_p + (1 - \lambda_{\text{surge}}) J_{T,\text{surge}}$$

$$J_{T,\text{sway}} = \lambda_{\text{sway}} J_p + (1 - \lambda_{\text{sway}}) J_{T,\text{sway}}$$

$$J_{T,\text{yaw}} = \lambda_{\text{yaw}} J_h + (1 - \lambda_{\text{yaw}}) J_{T,\text{yaw}}$$

where for $j \in \{\text{surge, sway, yaw}\}$, $\lambda_j \in [0, 1]$ weighs the relative importance between pose accuracy and control effort. These $\lambda_j$ weights can for instance be chosen in accordance with the performance level limits, such that the importance of pose accuracy increases with increasing distance from the pose goal. In general, they must take into account sea-state conditions, requirements for operational accuracy, as well as actuator limitations.

Finally, the total performance index $J_T \in [0, 100]$ is calculated as a weighted sum of the performance indices (1)-(3) for each DOF according to, e.g.,

$$J_T = \kappa_1 J_{T,\text{surge}} + \kappa_2 J_{T,\text{sway}} + \kappa_3 J_{T,\text{yaw}}$$

where $\sum_{i=1}^{3} \kappa_i = 1$. Nominally, $\kappa_i = \frac{1}{3} \forall i \in \{1, 2, 3\}$.
Having defined a measure of station-keeping performance, an autotuning procedure using this measure can now be developed. The proposed concept has been inspired by several approaches. First, it is desirable to combine the advantage of using previously acquired knowledge with the advantage of learning with an open mind. This approach can been seen as a combination of a gain-scheduling scheme, which only utilizes prior knowledge, and an adaptive scheme, which nominally does not take advantage of any earlier experience. A second inspiration has been the self-tuned, memory-based internal model control (IMC) PID control, see (Shah et al. 2000), (Yamamoto and Shah 2004), and (Takao et al. 2006), where experience-based parameters are stored and used as a local area for quick selection of controller parameters. In these papers, the area and parameters are only linked to the setpoint. However, this paper links these variables to the VOC since it will have more influence on the controller performance than only the setpoint for station-keeping operations. The idea is then that learning and training can be performed when the vessel is idle, while the gain-scheduling function allows for quick selection of good controller parameters according to the actual VOC during operations.

The proposed control functionality is illustrated in Figure 5, and works by the following procedure:

- **Initialization:** The controller is initialized with default parameters obtained from the sea trial. These parameters are used as initial values in the training, used in a default mode called normal, and also used as competitors during training.
- **Mode selection:** The controller has 3 main operating modes: normal, auto and training, which can be manually activated by the operator. The function of each mode is:
  - **Normal mode** (green), where the controller parameters are assigned the values derived from the sea trial. This mode can also be seen as a default or safe mode.
  - **Auto mode** (blue), where the controller parameters are changed dynamically according to the VOC in a gain-scheduling manner. Hence, a procedure for estimating the VOC is required.
  - **Training mode** (red), where the controller parameters are trained according to the current VOC. The goal of the training is to find the best possible parameters based on a performance index. The training can either be stopped by the operator, by a time limit, or if some predefined performance goal is achieved. Such a predefined goal can be linked up to historical data such as, e.g., historically best performance, etc.

Specifically, switching between the different controller modes are performed manually, and filters must be used to avoid large changes in the controller output when switching from one mode to another.

In our work, we use a fixed controller structure, which means that the training mode only explores the effect of different control parameters. Specifically, a nonlinear PID controller inspired by (Lindegaard 2003) is employed, also using the anti-windup scheme of (Visoli 2003) for robustness reasons.

Employing diagonal $K_p$, $K_d$, and $K_i$ matrices for the PID controller gains, and relating them to the parameters of natural frequency $\omega_n$ and relative damping ratio $\zeta$, we get the following relationship for each DOF (Fossen 2002)

$$k_{p,j} = \omega_{n,j}^2$$

$$k_{d,j} = 2\zeta\omega_{n,j}$$

$$k_{i,j} = \frac{\omega_{n,j}^3}{10}$$

where $j \in \{surge, sway, yaw\}$. Furthermore, the natural frequency $\omega_{n,j}$ can be related to the system bandwidth $\omega_{b,j}$ as

$$\omega_{b,j} = \omega_{n,j}\sqrt{1 - 2\zeta^2 + \sqrt{4\zeta^4 - 4\zeta^2 + 2}}$$

which, e.g., becomes equal to $\omega_{b,j} = 0.64\omega_{n,j}$ for $\zeta = 1$. Hence, the task of tuning the 3 PID parameters $k_{p,j}$, $k_{d,j}$, and $k_{i,j}$ really boils down to tuning of the system bandwidth parameter $\omega_{b,j}$ when $\zeta$ has been chosen.

Assuming that the performance index (4) corresponds to a convex function, a rule-based search algorithm is used in the tuning procedure. Parameters that need to be defined for this algorithm include upper and lower bandwidths as well as start and stop search steps. The search then starts at a point and in a direction corresponding to the detected VOC and the chosen performance weight $\lambda_j$. Subsequently, a space of controller parameters is populated from these searches during the training mode, where each set of parameters is linked to a specific VOC and $\lambda_j$ value. In auto mode, the relevant parameters are then applied to control the vessel. See (Alme 2008) for further details.
4. CASE STUDY: STATION KEEPING OF AN OFFSHORE SUPPLY VESSEL

Several simulation scenarios involving a dynamic model of the fully actuated offshore supply vessel Northern Clipper are explored in (Alme 2008). Due to space restrictions, only one of them will be mentioned here. This scenario involves tuning of the surge DOF for sea state 5, corresponding to rough sea with a significant wave height of 4 m; a 0.5 m/s strong current; and a_{surge} = 0.5. The pose accuracy and control effort are thus weighted equally in the performance index. Furthermore, the passive nonlinear observer described in (Fossen 2002) is employed as a filter and state estimator, and saturation limits are enforced on the actuators. With \( \zeta_{surge} = 1 \) and using a time window of 5 minutes, the autotuning performance of Figure 6 is obtained. Hence, the best bandwidth for this scenario is found after 7 iterations, i.e., 35 minutes.

5. CONCLUSIONS

This paper has considered several aspects related to the problem of automatic tuning of DP controllers for marine surface vessels. Since a controller with fixed gains cannot behave optimally for all VOCs, autotuning can prove to be very valuable in practice, saving time for commissioning and improving operational robustness. This work reviewed some previous work and discussed fundamental concepts within the subject area. Also, a novel performance index for station keeping was proposed and applied together with an autotuning algorithm using data generated from the index. Finally, some simulation results concerning station keeping of an offshore supply vessel operating in challenging sea-state conditions were included.

REFERENCES


