DP INNOVATION

Automatic Tuning of a DP Vessel

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L-3 Communications Dynamic Positioning and Control Systems

October 7-8, 2008

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Automatic Tuning of a DP Vessel

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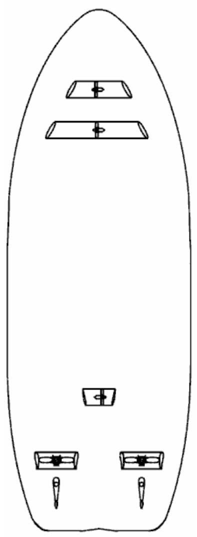
INTRODUCTION

• steps to tuning a DP control system:
1.fine-tune math models of the vessel and actuators
2.fine-tune controller parameters (e.g. PID gains)

• this presentation elaborates on Step 1

• tuning of the math models can be performed manually by an analyst, or using parameter estimation software

• any steps that can be performed by an analyst can theoretically be automated with equal or greater accuracy



equations of motion, etc.

THE MATHEMATICAL MODELS

KINEMATICS OF THE 3 DOF MODEL

- *ν* ("nu") is the ship's velocity in the relative frame

- *η* ("eta") is the ship's position in the fixed frame

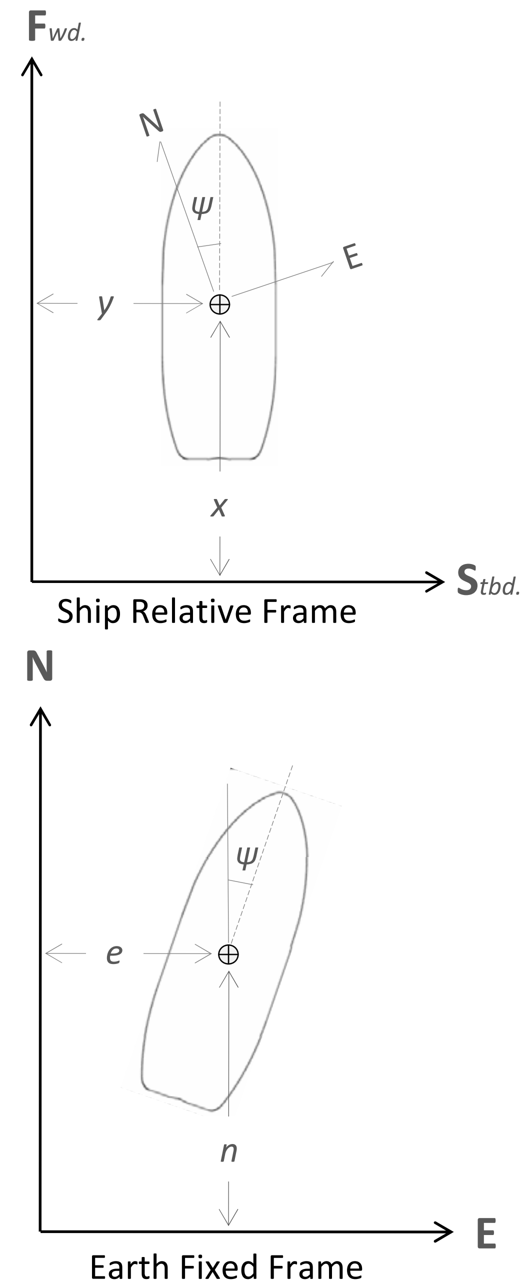
- *R* is a coordinate transformation matrix

- ***x*** is the full state vector

$$\boldsymbol{x} \equiv \begin{bmatrix} \eta \\ \nu \end{bmatrix}, \quad \dot{\boldsymbol{x}} = \begin{bmatrix} R\nu \\ \dot{\nu} \end{bmatrix}$$

$$\eta \equiv \begin{bmatrix} n \\ e \\ \psi \end{bmatrix} = \overbrace{\begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}}^{R} \cdot \begin{bmatrix} x \\ y \\ \psi \end{bmatrix}$$

$$\nu \equiv \begin{bmatrix} u \\ v \\ r \end{bmatrix} \equiv \overbrace{\begin{bmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}}^{R^{-1}} \cdot \begin{bmatrix} \dot{n} \\ \dot{e} \\ \dot{\psi} \end{bmatrix}$$



DYNAMICS OF THE 3 DOF MODEL

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

- the dynamics model[1] is expressed in the ship relative frame

- *M* is a mass matrix

- *C(v)*, a Coriolis matrix, is nearly zero during DP maneuvers and may be neglected[2]

- *D* is a damping matrix

- *τ* and *ω* are control input and disturbance vectors, respectively

$$M = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix}$$

$$C(\nu) = \begin{bmatrix} 0 & 0 & -m_{22}v - m_{23}r \\ 0 & 0 & m_{11}u \\ m_{22}v + m_{23}r & -m_{11}u & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & d_{23} \\ 0 & d_{32} & d_{33} \end{bmatrix}$$

PROPELLER MODEL

- ω is the shaft velocity of the propeller

- p is the pitch, or blade angle, of the propeller

- p_0 is the "zero-thrust" pitch value

- k_2 is the "pitch-to-thrust" exponent

- k_3 is the reverse efficiency factor

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

General Case ("combinator")

$$T = \begin{cases} T_{\max} \dfrac{(p - p_0)^{k_2}}{\Delta p_{\max}} & p - p_0 \geq 0 \\ -k_3 T_{\max} \dfrac{(p_0 - p)^{k_2}}{\Delta p_{\max}} & p - p_0 < 0 \end{cases}$$

Fixed RPM

SELECTION OF UNKNOWN MODELING CONSTANTS

Unknown Constants	Symbols
coefficients of the D matrix	$d_{11,}$ d_{22}, d_{23}, d_{32}, d_{33}
pitch-to-thrust exponent, main props	k_2
reverse factor, main props	k_3
zero-force pitch, main props	p_0
center of gravity, longitudinal	x_{cg}
maximum thrust, tunnel thrusters	$T_{1,max}$, $T_{2,max}$, $T_{3,max}$
rudder parameters	*[not discussed here]*

- ideally, every model parameter should be identified by the estimator
- realistically, we only identify the most uncertain constants
- due to relative size, main propellers receive special attention

DP tuning “by hand”

HUMAN ESTIMATION METHODS

Reverse efficiency factor, main propellers

JOYSTICK METHOD

• main propellers are "biased" against each other while adjusting thrust levels until zero net force is observed

• method is sensitive to environmental forces

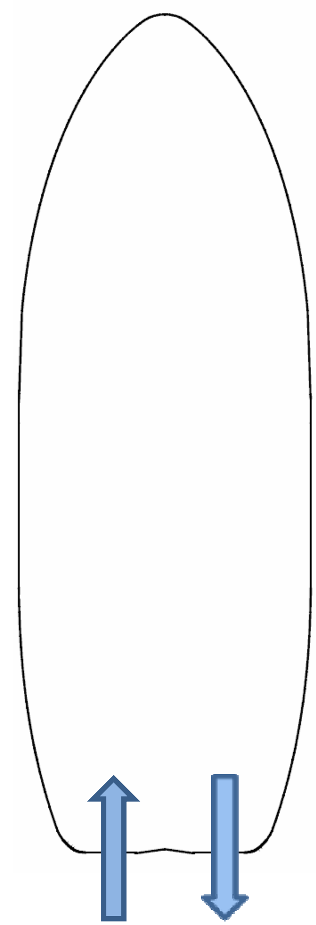
DP METHOD

• ahead-thrusting main is held at a fixed thrust level

• astern-thrusting main is controlled by DP system to hold station

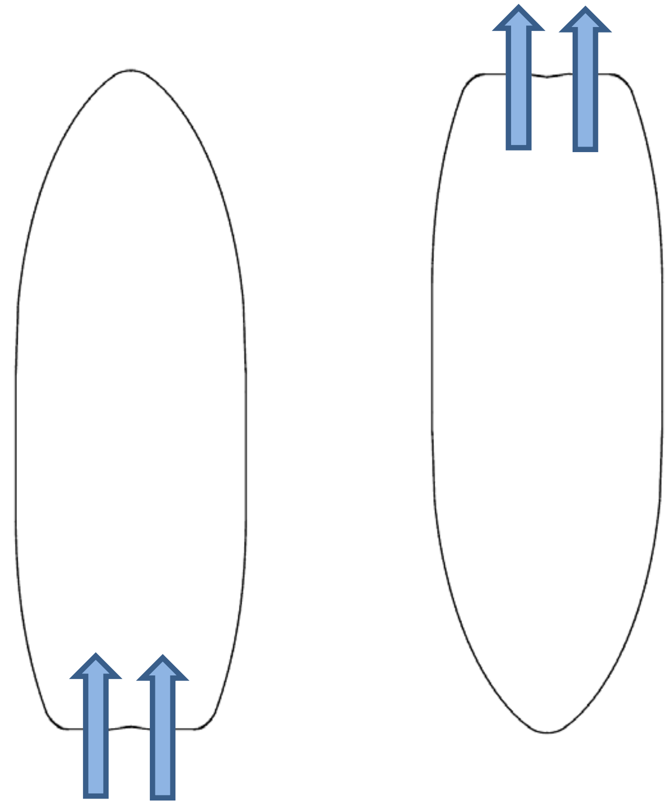
• reverse factor is adjusted until vessel is unaffected by changes in the fixed thrust level of the ahead-thrusting main

• method is time-consuming



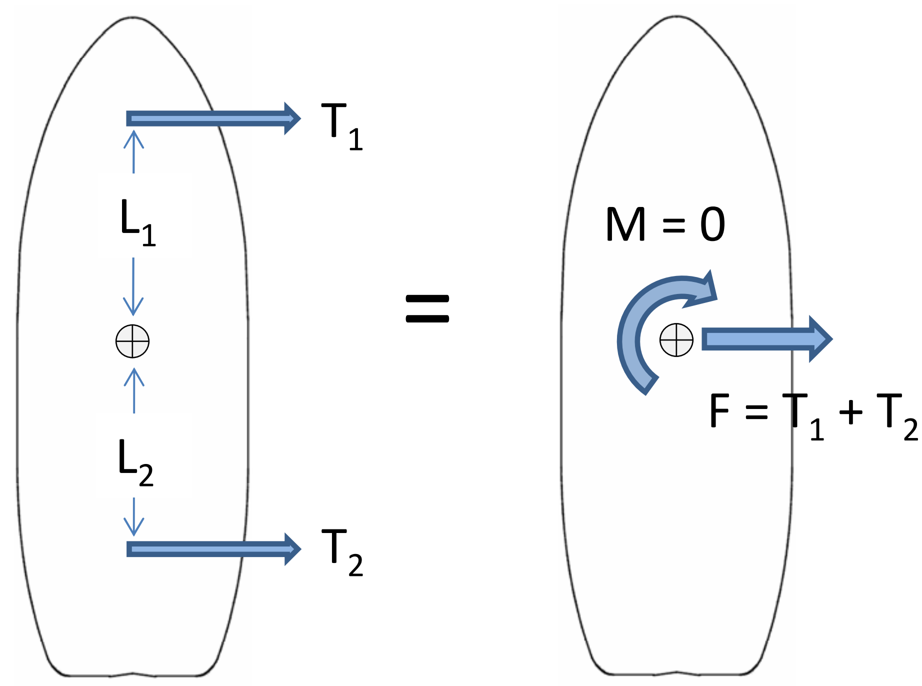
Main propeller pitch offset

- vessel holds its position at opposite headings
- average surge commands recorded
- adjust p_0 , repeat until equal forces achieved
- inaccurate and **time consuming**
- sensitive to inconstant environments



Center of Rotation

- sway motions are executed while adjusting x_{cg} until no yaw coupling is observed
- if thruster ratings are not accurate, the true center of mass cannot generally be identified
- for example: 30% error in T_2 corresponds to 5m error in x_{cg} (for a 70m vessel).



maneuvers and algorithms

COMPUTER ESTIMATION METHODS

THE INVERSION PROBLEM

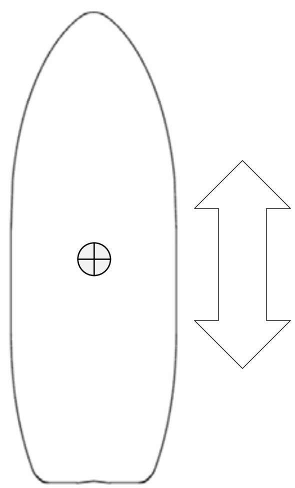
1. Record data from various maneuvers:
   - how to choose the best maneuvers?
   - sensitivity to unknown environmental forces?
   - maneuvers should be simple

2. Apply an estimation algorithm to “fit” the model to the real data:
   - EKF
   - UKF
   - least squares minimization

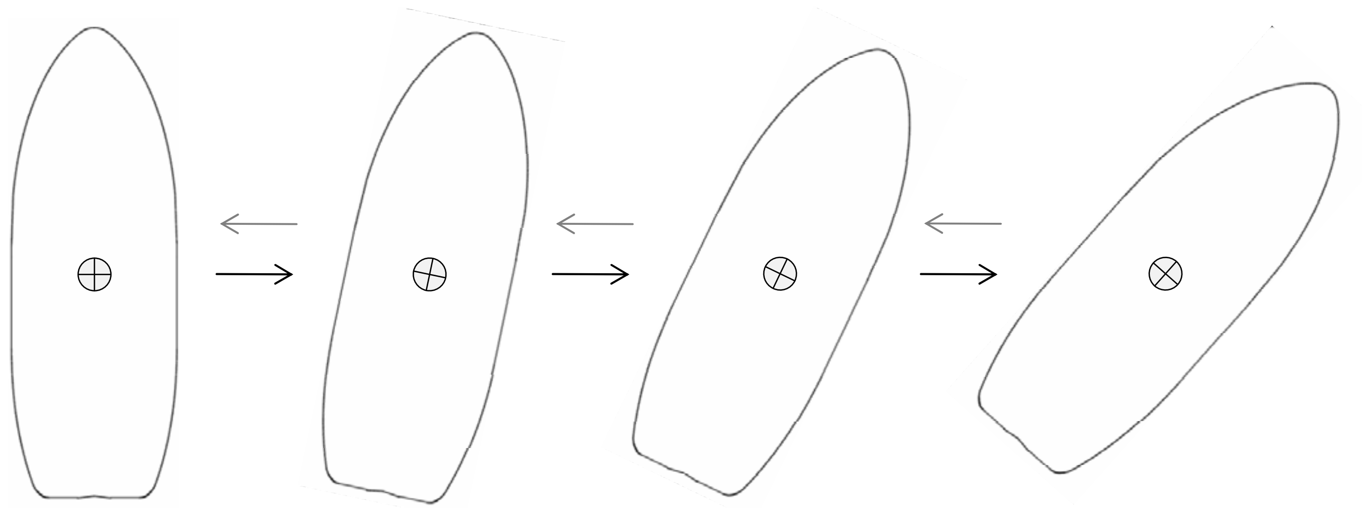
ESTIMATION MANEUVERS

*maneuvers performed twice, at reciprocal headings

Decoupled surge phase



Coupled sway-yaw phase



UNSCENTED KALMAN FILTER

- reportedly an improvement over EKF in many cases
- roughly the same computation effort as EKF
- does not require linearization of the ODEs
- failed to converge to an answer using real data
- appears unsuitable for this application

LEAST SQUARE METHODS

- commonly used in offline parameter estimation formulations

- can be computationally intensive

- unlike a recursive formulation such as Kalman, these algorithms have access to all the recorded data at each iteration

- bounds easily applied to estimates, guaranteeing a feasible solution

LEAST SQUARES FORMULATION

- thruster commands, *u* and position data, *η*, sampled with period *Δt*:

$$\hat{u}_k \equiv u(t_0 + k\Delta t) + \mu_k, \qquad \hat{\eta}_k \equiv \eta(t_0 + k\Delta t) + \nu_k,$$

- curve fitting is applied to the position data to obtain the full state estimate $\tilde{x}$

- for a given parameter set, *p*, a model trajectory is calculated:

$$\dot{x}(t) = f(x(t), u(t), p)$$

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

- next we minimize residuals, *e,* between real position data and the model trajectory

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

subject to $p_{\min} \leq p \leq p_{\max}$, where $e_i \equiv \hat{\eta}_i - diag([1\,1\,1\,0\,0\,0]) \cdot x_i$

and $$W = diag([1\,1\,\tfrac{180}{\pi}])$$

LEAST SQUARES ESTIMATION RESULTS

Parameter	Estimated Value*	Expected Value*
d_{11}	0.0054	0.0358
d_{22}	0.0798	0.1183
d_{23}	0.0150	-0.0124
d_{32}	-0.0101	-0.0041
d_{33}	0.0117	0.03080
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}	*0.0083 aft of nominal*	*0*
$T_{max,2}$	0.001387	0.001663
$T_{max,3}$	0.001664	0.001663

**normalized (Bis-system)*

CONCLUSIONS

- Least squares minimization seems preferable to Kalman filter for DP tuning problems of increasing complexity

- this closed-loop formulation is a promising step towards total automation of the DP tuning process

THANK YOU