## **Identification of Parameters for Tethered Satellite System to Emulate Net-Captured Debris Towing**

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7th International Conference on Tethers in Space June 2-5, 2024, York University, Toronto, Canada





Introduction

Systems Description and Modeling

Parameter Identification

Analysis of Results





- Introduction
- Systems Description and Modeling
- Parameter Identification
- Analysis of Results

Conclusion

- Increasing amounts of space debris pose threats to spacecraft operations
  - Many potential systems for Active Debris Removal have been proposed (Shan et al., 2017)
    - Harpoon-Based
    - Robotic-Arms-Based
    - Net-Based
  - Tether-nets are particularly promising
    - Safe capture of large, tumbling objects
  - How can we study them?
    - Simulation and analysis



Figure from (Botta et al., 2019)

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Introduction

- **Motivation:** Need a **simplified model** of the chaser-net-target system for long-duration orbital simulations.
  - High-fidelity simulations with net  $\rightarrow$  very high computational cost
- Model Approximation:
  - The net is replaced with *4 tethers* rigidly connected to the target.
  - Need to *identify the appropriate properties* of the sub-tethers (STs) + tethers connection point mass of the lower-order model that *best represent* the high-fidelity dynamics.





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### Net Capture System and Target Debris

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- Net modeled via the lumped-parameter modeling method
  - Computational challenge: The entire system often involves 1000+ degrees of freedom
- **Corner masses** used to guide the net to the target.
- Net includes a **closing mechanism**, attached to the chaser by the **main tether (MT) and winch**.
- Sliding-mode attitude controller present on the cubic chaser to maintain desired orientation.
- Target debris: Zenit-2 rocket upper stage

Net simulator detailed within (Botta et al., 2019)



### Sub-Tether Tethered Satellite System

- Chaser and debris are **rigid bodies** with the same dimensions as with the high-fidelity model.
- All tethers modeled as nonlinear spring-damper (Kelvin–Voigt) elements.
  - MT is given the *same length, stiffness, and damping properties* as with the high-fidelity model.
- Connection point P links the MT to the 4 STs.
  - Modeled as a point mass
- Sliding-mode attitude controller present on the cubic chaser to maintain desired orientation.



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### **Parameter Identification**

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### **Parameter Identification**

- Parameter Identification Process:
  - Perform 6 high-fidelity debris towing simulations
    - 3 for parameter identification via solving optimization problems.
    - **3 for validation** of the parameters on unseen data.
    - Use all same initial conditions, except for *initial target angular velocity.*
  - Perform optimization to determine the lower-order model parameters which minimize dynamics difference with the high-fidelity model.
    - 2 cost functions defined for the task





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### **Design Variables**

- Thread stiffness of the STs:  $s_1 = \log_{10}(k_{ST})$ 
  - $1 \le s_1 \le 4$
- Thread length of the STs:  $s_2 = L_{ST}$ , m
  - $6 \le s_2 \le 16$
- Thread damping of the STs:  $s_3 = \log_{10}(c_{ST})$ 
  - $0 \le s_3 \le 4$
- Percent of Net Mass Distributed to the Connection Point: ۲  $m_P = s_4 m_{net}$ , kg
  - Rest of the net mass distributed to the target:
    - $m_{target} = m_{target,0} + (1 s_4)m_{net}$ , kg
  - $0.1 \le s_4 \le 1$

- Bounds to **limit the search space** of the optimization.
  - Chosen based on values the parameters are expected to lie within.
- Stiffness and damping parameters of the STs scaled by  $\log_{10}$  () functions  $\rightarrow$  allow values to be of similar magnitude to other parameters.
  - To aid the optimization solver in finding solutions.



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 $r_D^{\mathcal{H}}$ 

 $r_D^{\mathcal{L}}$ 

#### **Cost Functions**

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$$\begin{aligned} \mathbf{r}_{D/C}^{\mathcal{H}} &= \mathbf{r}_{D/O}^{\mathcal{H}} - \mathbf{r}_{C/O}^{\mathcal{H}} \qquad f_{1}(s) = \sum_{j=1}^{3} w_{1} \text{RMSE}_{r,j} + \\ \mathbf{r}_{D/C}^{\mathcal{L}} &= \mathbf{r}_{D/O}^{\mathcal{L}} - \mathbf{r}_{C/O}^{\mathcal{L}} \qquad w_{2}(\text{RMSE}_{\omega_{D},j} + \text{RMSE}_{\omega_{C},j}) \\ \mathbf{r}_{\Delta} &= \mathbf{r}_{D/C}^{\mathcal{L}} - \mathbf{r}_{D/C}^{\mathcal{H}} \qquad w_{2}(\text{RMSE}_{\omega_{D},j} + \text{RMSE}_{\omega_{C},j}) \\ \mathbf{\omega}_{C,\Delta} &= (^{\mathcal{O}} \mathbf{\omega}^{\mathcal{C}})^{\mathcal{L}} - (^{\mathcal{O}} \mathbf{\omega}^{\mathcal{C}})^{\mathcal{H}} \qquad \text{RMSE}_{r,j} = \sqrt{\sum_{g=1}^{N} \frac{||\mathbf{r}_{\Delta,j,g}||^{2}}{N}} \\ \text{RMSE}_{\omega_{D},j} &= \sqrt{\sum_{g=1}^{N} \frac{||\mathbf{\omega}_{D,\Delta,j,g}||^{2}}{N}} \\ \text{RMSE}_{\omega_{C},j} &= \sqrt{\sum_{g=1}^{N} \frac{||\mathbf{\omega}_{C,\Delta,j,g}||^{2}}{N}} \end{aligned}$$

 $(.)^{\mathcal{H}}$ : High-fidelity model quantities  $(.)^{\mathcal{L}}$ : Lower-order model quantities

- Cost Function 2: Difference in the MT tension between models.
  - MT tensions *dependent on the relative* ٠ **dynamics**  $\rightarrow$  may indirectly enable the relative dynamics to be as identical as possible.

$$f_2(s) = \sum_{j=1}^3 \text{RMSE}_{T,j}$$

$$\text{RMSE}_{T,j} = \sqrt{\sum_{g=1}^{N} \frac{(T_j^{\mathcal{H}} - T_j^{\mathcal{L}})^2}{N}}$$



### **Optimization Problem Formulation**

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# $\min_{s} f_k(s)$ where: $s = [s_{1,}s_{2,}s_{3,}s_4], k = 1, 2$ $s_{j,LB} \le s_j \le s_{j,UB}$ Chosen Solver

#### Notes:

- Do not know the shapes of the cost functions
  - Likely *nonconvex* with respect to the design variables
  - Gradients unknown
- Nonlinear programming problem
- No constraints given on the value of the cost functions
  - Only upper and lower bounds given to design variables

#### Mesh Adaptive Direct Search (MADS)

- Derivative-free optimization solver
- Utilized in many scientific and engineering application
  - (Alarie et al., 2021)
- Requires an initial guess to be given



#### **Analysis of Results**

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### **Converged Optimization Results**

- **Converged design variables differ** based on the choice of initial guesses.
  - More drastic change using Cost Function 2 compared to 1 for different initial guess.

Converged Cost Function Values for Training Dataset

d		_			-			
adoling			Obj. Function	Initial Guess 1	Initial Guess 2	Initial Guess	3 Initial Guess 4	Initial Guess 5
Juening			$f_1(\mathbf{s})$	10.3854	10.3915	10.3824	10.3853	10.3859
			$f_2(s)$	272.03	292.99	292.46	272.15	292.818
rameter		Converged	Decision Variab	es Using $f_1(s)$				
entification	Best Converge Cost		Variables	Initial Guess 1	Initial Guess 2	Initial Guess 3	Initial Guess 4	Initial Guess 5
	Function 1 value and		<i>s</i> <sub>1</sub>	1.3942	1.3932	1.3948	1.3943	1.3943
	design variables		<i>s</i> <sub>2</sub>	6.5288	6.5180	6.5406	6.5281	6.5282
			$s_3$	1.3114	1.3058	1.3257	1.3145	1.3131
alysis of			<i>s</i> <sub>4</sub>	0.5602	0.7534	0.2726	0.55 <mark>4</mark> 6	0.5832
sults		Comment		les lleiner f (s)				
	Best Converge Cost	Converged	Decision variab	lies Using $f_2(s)$				
	Eurotion 2 value and		Variables	Initial Guess 1	Initial Guess 2	Initial Guess 3	Initial Guess 4	Initial Guess 5
onclusion			<u>s</u> 1	2.7398	1.0409	2.5097	2.7454	1.1012
	design variables		<i>s</i> <sub>2</sub>	8.5805	9.1683	6.5366	8.6522	9.1923
			<i>s</i> <sub>3</sub>	2.1721	2.8961	2.3678	2.1952	2.8975
			S <sub>4</sub>	1.0000	0.5933	0.3817	0.1608	0.1371

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### **Converged Optimization Results**

- **Converged design variables differ** based on the choice of initial guesses.
  - More drastic change using Cost Function 2 compared to 1 for different initial guess.
  - Evaluating cost functions using validation dataset + converged design variables yielded similar costs. Cost Function Values for Validation Dataset

l		Obj. Functi	on _Initial Guess	1 Initial Guess	2 Initial Gues	s_3 _ Initial Gues	s 4 Initial Guess
uenng		$f_1(s)$	11.8821	11.8982	11.8601	11.8814	11.8826
		$f_2(\mathbf{s})$	293.37	287.97	326.78	290.73	288.55
amatar		Converged Decision Varia	bles Using $f_1(s)$		1.0.00		
ntification	Best Converge Cost	Variables	Initial Guess 1	Initial Guess 2	Initial Guess 3	Initial Guess 4	Initial Guess 5
	Function 1 value and	<u> </u>	1.3942	1.3932	1.3948	1.3943	1.3943
	design variables	s <sub>2</sub>	6.5288	6.5180	6.5406	6.5281	6.5282
		<i>s</i> <sub>3</sub>	1.3114	1.3058	1.3257	1.3145	1.3131
alysis of		<i>s</i> <sub>4</sub>	0.5602	0.7534	0.2726	0.5546	0.5832
	Deat Converge Cost	Converged Decision Varia	bles Using $f_2(s)$				
	Best Converge Cost	Variables	Initial Guess 1	Initial Guess 2	Initial Guess 3	Initial Guess 4	Initial Guess 5
nclusion	Function 2 value and	<i>s</i> <sub>1</sub>	2.7398	1.0409	2.5097	2.7454	1.1012
	design variables	<i>s</i> <sub>2</sub>	8.5805	9.1683	6.5366	8.6522	9.1923
		<i>s</i> <sub>3</sub>	2.1721	2.8961	2.3678	2.1952	2.8975
		$s_4$	1.0000	0.5933	0.3817	0.1608	0.1371



#### Sample Scenario Comparison

• Overall **dynamics similar** between the models

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• Chaser attitude in the high-fidelity model less stabilized than in the lower-order simulations



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#### Sample Scenario Comparison

• Overall **dynamics similar** between the models

results in *better MT tension matching*.

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• Parameters from Cost Function 1 results in better relative dynamics matching; Cost Function 2

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#### Sample Scenario Comparison

Overall dynamics similar between the models

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- High-fidelity *chaser attitude dynamics is less stabilized* compared to both lower-order simulations.
- Using parameters from Cost Function 1 results in *better debris angular rates matching*. ۲





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- **Parameter identification framework** proposed to allow lower-order TSS model to best approx. net-based debris towing.
- Two optimization cost functions were formulated to minimize the difference in dynamics quantities of interest between models.
  - Lower-order TSS with determined parameters demonstrated *satisfactory dynamics matching performance*.
- Compared to Cost Function 2, Cost Function 1 demonstrated:
  - Less sensitivity to initial guesses
  - Better overall dynamics matching (except MT tension).
- **Future work:** Apply the framework to larger datasets with **larger variations** in the simulation's initial conditions.

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### Thank you!

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This work is supported by NSF Award CRII Award No.2105011. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

The authors express gratitude toward CM Labs Simulations for providing licenses for the Vortex Studio simulation framework. The authors would like to thank Liam Field for providing the LVLH frame system visualization code.





#### **Systems Parameters and Initial Conditions**

System Parameters For Both High-Fidelity and Lower-Order Simulations

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Variables	Value	Units
Chaser Mass, $m_C$	1600	kg
Nominal Debris Mass, $m_D$	9000	kg
Chaser Side Length, $L_C$	1.5	m
Debris Length, $L_D$	11	m
Debris Diameter, $d_D$	3.9	m
Chaser Inertia Matrix, $J_C$	diag(266.67, 266.67, 266.67)	$kgm^2$
Debris Inertia Matrix, $J_D$	diag(94880, 94880, 46295.5)	$kgm^2$
Chaser Attachment Point, $[r_{A1/C}]_C$	$[0, 0, -0.75]^T$	m
Debris Attachment Point 1, $[r_{1/D}]_D$	$[-1.9500, 0, -5.7170]^T$	m
Debris Attachment Point 2, $[r_{2/D}]_D$	$[-1.9500, 0, 5.2830]^T$	m
Debris Attachment Point 3, $[r_{3/D}]_D$	$[1.9500, 0, -5.7170]^T$	m
Debris Attachment Point 4, $[r_{4/D}]_D$	$[1.9500, 0, 5.2830]^T$	m
Main-tether Stiffness, $k_{MT}$	3000	N/m
Main-tether Damping, $c_{MT}$	300	Ns/m
Main-tether Natural Length, $l_{MT}$	15.0	m
Time for chaser thrust to reach maximum, $t_{slope}$	50	S

Initial Conditions For the High Fidelity Simulations

Variables	Value	Units
<b>r</b> <sub>C/0</sub>	$[4.95199, -1.0547469, -4.65022589]^T \times 10^6$	m
${}^{\mathcal{O}}\boldsymbol{v}_{C/O}$	$[4.771333506, 4.267936104, 4.119936176]^T \times 10^3$	m/s
$q_{C}$	$[0.506372, 0.628113, -0.5865386, -0.0709467]^T$	-
$\bar{\mathcal{O}}_{\boldsymbol{\omega}}^{C}$	$[-0.0085526588, 0.019837, 0.0020484]^T$	rad/s
<b>r</b> <sub>D/O</sub>	$[4.952002, -1.054735, -4.650215]^T \times 10^6$	m
$^{\mathcal{O}}\boldsymbol{v}_{D/O}$	$[4.771338, 4.267935, 4.1199337]^T \times 10^3$	m/s
$q_D$	$[0.3834407, 0.4526303, 0.7957778, 0.12180569]^T$	-
$\mathcal{O}_{\boldsymbol{\omega}}^{\mathcal{D}}$	$  ^{\mathcal{O}}\boldsymbol{\omega}^{\mathcal{D}}(0)   \cdot [0.0047695, -0.9999851, 0.002652839]^T$	rad/s
<b>r</b> <sub>P/O</sub>	$[4.951991, -1.05474644, -4.6502254]^T \times 10^6$	m
OV DIO	$[4.771333506, 4.267936104, 4.119936176]^T \times 10^3$	m/s



### **Converged Optimization Results**

Provided Initial Guess

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List of Initial Decision Variables Given to The Optimization Solver

Variables	Initial Guess 1	Initial Guess 2	Initial Guess 3	Initial Guess 4	Initial Guess 5
<i>s</i> <sub>1</sub>	3	2	3	3	3
$s_2$	9	9	8	9	9
<i>s</i> <sub>3</sub>	1	1	1	2	1
s <sub>4</sub>	0.5	0.5	0.5	0.5	0.75

Best converged design variables are converted and displayed as physical parameters below:

Parameter	$f_1(\mathbf{s})$	$f_2(\mathbf{s})$
$k_{ST}$ ,N/m	24.819	549.28
$l_{ST}$ , m	6.5406	8.5805
$c_{ST}$ , Ns/m	21.169	148.627
$m_p$ , kg	0.7449	2.7326

• Initial Debris Angular Speed for different simulations:

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Simulation #	$  ^{\mathcal{O}}\boldsymbol{\omega}^{\mathcal{D}}(0)  $
1	0.16654 rad/s
2	0.16151 rad/s
3	0.15985 rad/s
4	0.15301 rad/s
5	0.14948 rad/s
6	0.14622 rad/s