A General Framework for Trajectory Optimization with Respect to Multiple Measures

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Technical Presentation
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- Multi-sensor navigation
- GPS alternatives such as vision
- Competition for better algorithms
- Greater accuracy at a lower cost
- Nonlinear filtering
- Open source development

TOMMAS

Trajectory Optimization Manager for Multiple Algorithms and Sensors

Mission Statement











"Deliver a software testbed that helps a user to define *optimal* for a specific navigation problem by selecting components from a library of dynamic models, sensing algorithms, and optimization algorithms."









Potential Benefits

For the Systems Engineer

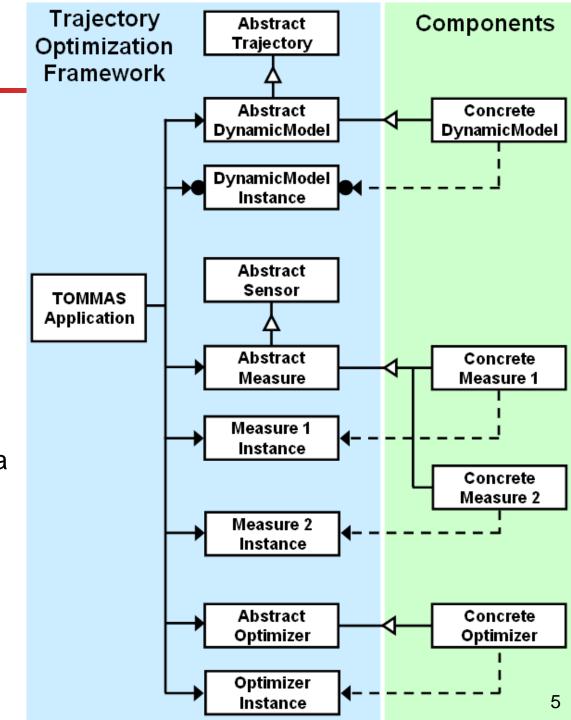
- Ease of creating Interface Control Documents (ICDs).
- Automated testing of algorithms and sensors together.
- Encouraging innovation by leveling the playing field.
- Lower cost GOTS devices due to commoditization in long-term.

For the Warfighter

- Convenience of device interoperability and potential hot-swapping.
- Mitigates sensor cutouts by augmenting GPS/INS with cameras, altimeters, LIDAR, RF signals of opportunity, etc.



- Break existing solutions into interchangeable parts.
- Use object-oriented design to create abstract interfaces in C++, Matlab, and Python.
- Implement polymorphism via the Factory Design Pattern.



Navigation by Trajectory Optimization

Assumptions

- Newtonian mechanics
- Global reference frame
- Rigid body dynamics
- Time domain $[t_0, t_K]$
- 6-DoF range in $\mathbb{R}^3 \times \mathbb{S}^3$
- Finite forces (C¹ continuity)

Given

- Stochastic dynamics
- Multiple calibrated sensors

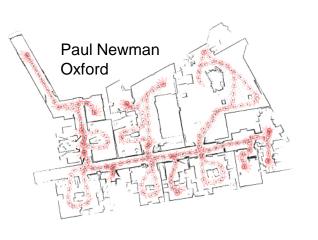
Find

- Maximum likelihood trajectory
- Accuracy of results



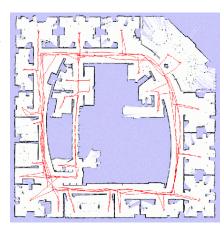
Framing the Navigation Problem

Efficient solutions to sub-problems exist in the literature (some also map the environment):





Michael Kaess GA Tech / MIT

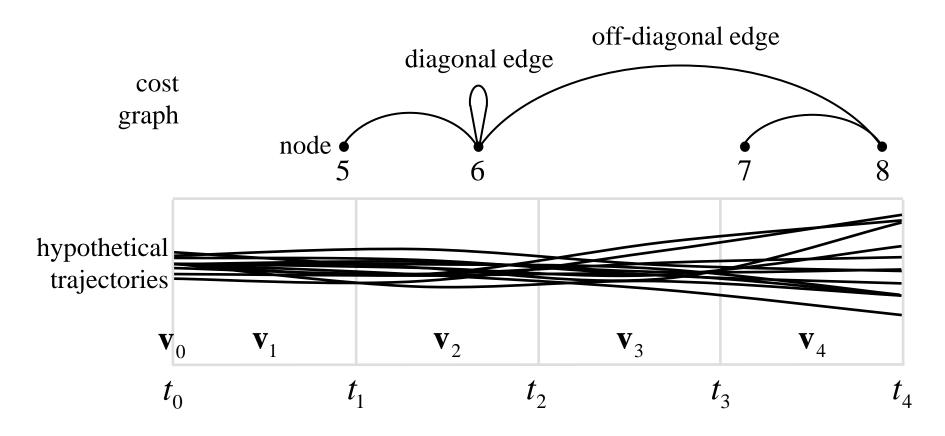


The generalized problem can be expressed in this form:

$$\mathbf{v}^* = \operatorname*{argmin}_{\mathbf{v} \in \mathbb{V}} \left\{ \sum_{k \in \mathbb{K}} r(\mathbf{v}, k) + \sum_{m \in \mathbb{M}} \sum_{(a,b) \in \mathbb{A}} s_m(\mathbf{u}, \mathbf{x}, (a,b)) \right\}$$

$$\mathbf{x} = \mathbf{F}(\mathbf{v}, \mathbf{u})$$

Visualizing the Problem Structure

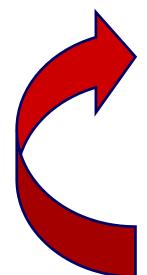


- Each block of parameters corresponds to a discrete time period.
- Measurements have graph structure (node = time, edge = measure).
- Trajectories are not required to have a graph structure.



Optimization Concept

Step 1) Generate initial parameters.



Step 2) Compute prior costs from DynamicModel.

Step 3) Compute costs from each Measure.

Step 4) Generate new parameters.

Within this framework, there are many possible strategies:









Gradient

Genetic

Simplex

Other

DynamicModel Details

Stochastic motion model in nonlinear functional form:

$$\mathbf{x} = \mathbf{F}(\mathbf{v}, \mathbf{u})$$

- Can depend on sensor data (i.e. strapdown mechanization):
- Driven by parameters v that are not known in advance (i.e. noise, disturbance, perturbation).
- Prior statistical information about the parameters:

$$r(\mathbf{v},k) = -\log\left(\frac{\mathbf{P_{v}}(\mathbf{v}|k)}{\|\mathbf{P_{v}}(\mathbf{v}|k)\|_{\infty}}\right)$$

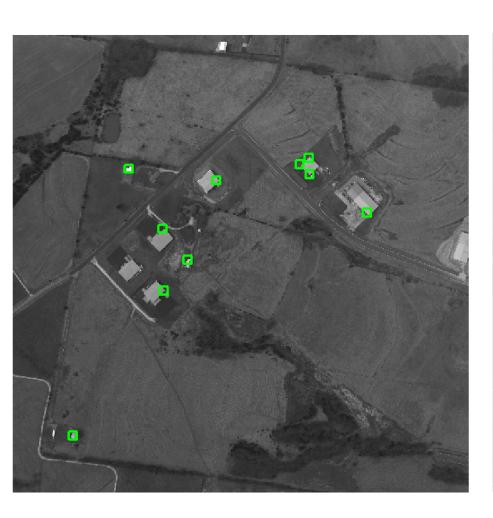
Measure Details

Sensing model in nonlinear functional form:

$$s_{m}(\mathbf{u}, \mathbf{x}, (a,b)) = -\log \left(\frac{P_{\mathbf{u}|\mathbf{v}}(\mathbf{u}|\mathbf{x}, (a,b), m)}{\|P_{\mathbf{u}|\mathbf{v}}(\mathbb{U}|\mathbf{x}, (a,b), m)\|_{\infty}} \right)$$

- It evaluates how much the data deviates from a statistical model given the trajectory.
- As a mathematical measure, it systematically assigns nonnegative numbers (costs) to each element in its domain. The domain is the space of possible data.
- Multiple points in the trajectory space may map to the same point in the measure space, so a measure may not be sensitive to some trajectory deviations.

Incremental Measure: Visual Tracking



Feature Sampling

Epipolar Projection



Participation Participation

- Use the framework for free under a permissive license agreement.
- Contribute as a developer and stay on the cutting edge.
- Own the intellectual property for components that you produce.
- Download the code from our open source repository.

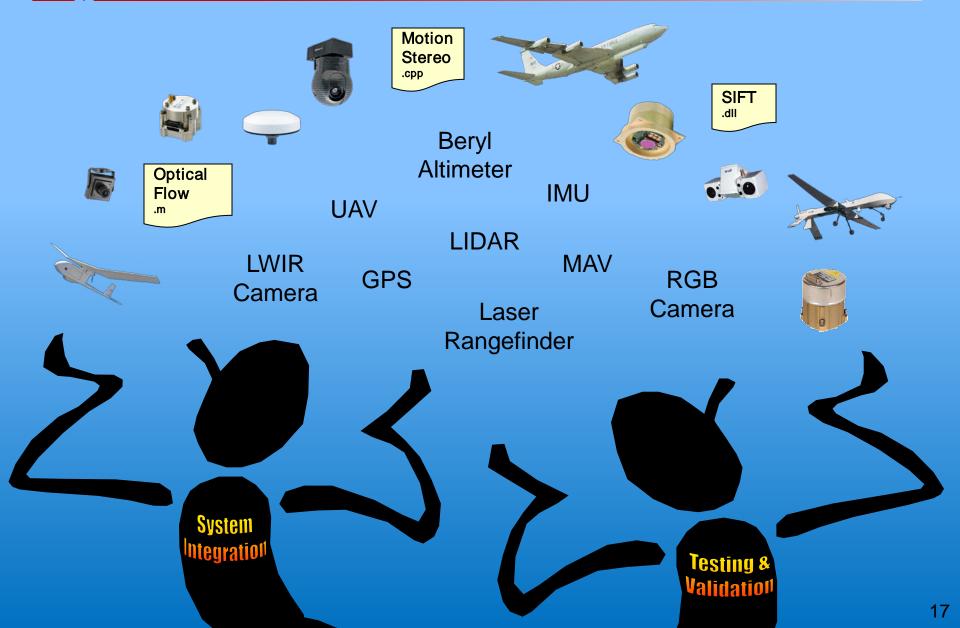
Keyword on Google Code:

functionalnavigation

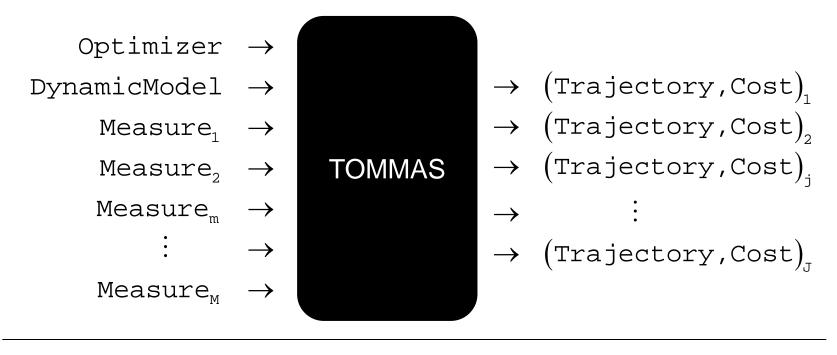
functionalnavigation

(Additional Slides)

Managing Multiple Algorithms and Sensors



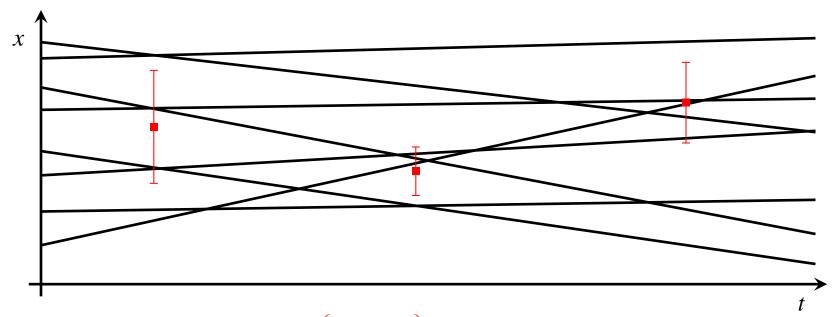
System Integrator Perspective



Configuration Set

Solution Set

Trajectory Optimization: Weighted Least Squares



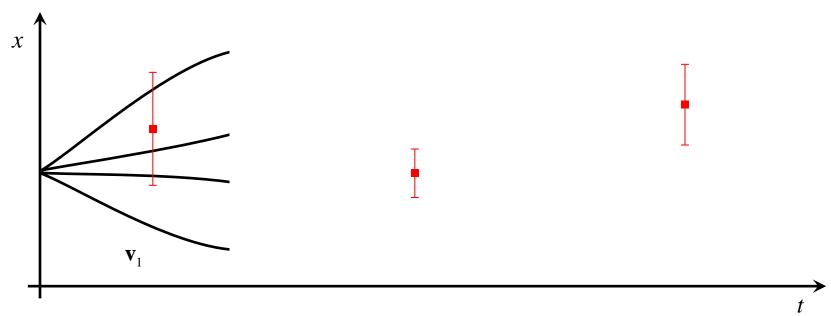
Sensor Data
$$\mathbf{u} = \begin{cases} t_0, t_1, t_2, \\ p_0, p_1, p_2, \\ \alpha_0, \alpha_1, \alpha_2 \end{cases}$$
 "Time, Position, and Weight"

Dynamic Model $\mathbf{x} = \mathbf{v}_0 + \mathbf{v}_1 t$ "Constant Velocity"

Functional Measure $s_0(\mathbf{u}, \mathbf{x}, (a, a)) = (\mathbf{x}(t_a) - p_a)^2 \alpha_a$ "Weighted Distance Squared"

Optimization Problem
$$\mathbf{v}^* = \underset{\mathbf{v} \in \mathbb{R}^2}{\operatorname{argmin}} \left\{ \sum_{a=1}^3 s_0(\mathbf{u}, \mathbf{x}, (a, a)) \right\}$$
 "Weighted Least Squares"

Trajectory Optimization: Weighted Least Squares



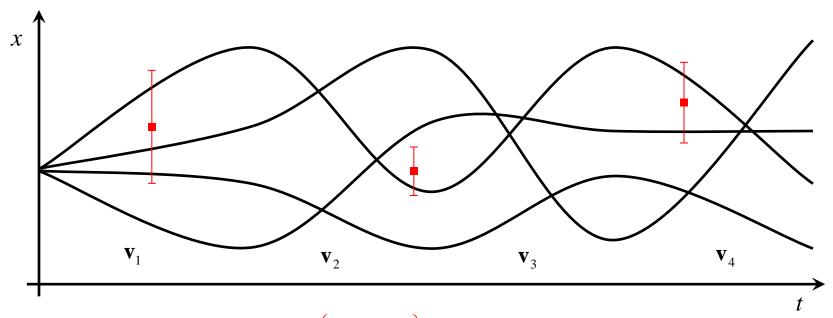
Sensor Data
$$\mathbf{u} = \begin{cases} t_0, t_1, t_2, \\ p_0, p_1, p_2, \\ \alpha_0, \alpha_1, \alpha_2 \end{cases}$$
 "Time, Position, and Weight"

Dynamic Model $\mathbf{x} = \mathbf{F}(\mathbf{v}, \mathbf{u})$ "Generalized Rigid Body Dynamics"

Functional Measure $s_0(\mathbf{u}, \mathbf{x}, (a, a)) = (\mathbf{x}(t_a) - \mathbf{p}_a)^2 \alpha_a$ "Weighted Distance Squared"

Optimization Problem
$$\mathbf{v}^* = \underset{\mathbf{v} \in \mathbb{V}}{\operatorname{argmin}} \left\{ \sum_{a=1}^{3} s_0(\mathbf{u}, \mathbf{x}, (a, a)) \right\}$$
 "Weighted Least Squares"

Trajectory Optimization: Generalized Least Squares



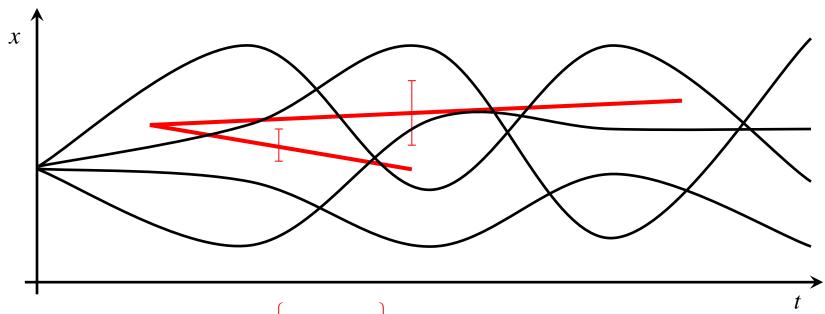
Sensor Data
$$\mathbf{u} = \begin{cases} t_0, t_1, t_2, \\ p_0, p_1, p_2, \\ \alpha_0, \alpha_1, \alpha_2 \end{cases}$$
 "Time, Position, and Weight"

Dynamic Model $\mathbf{x} = \mathbf{F}(\mathbf{v}, \mathbf{u})$ "Generalized Rigid Body Dynamics" $r(\mathbf{v},k)$ "Prior Motion Information"

Functional Measure $s_0(\mathbf{u}, \mathbf{x}, (a, a)) = (\mathbf{x}(\mathbf{t}_a) - \mathbf{p}_a)^2 \alpha_a$ "Weighted Distance Squared"

Optimization Problem $\mathbf{v}^* = \operatorname*{argmin}_{\mathbf{v} \in \mathbb{V}} \left\{ \sum_{k \in \mathbb{K}} r(\mathbf{v}, k) + \sum_{n=1}^{3} s_n(\mathbf{u}, \mathbf{x}, (a, a)) \right\}$ "Weighted Least Squares with Prior"

Trajectory Optimization: Relative Least Squares



Sensor Data
$$\mathbf{u} = \begin{cases} t_0, t_1, t_2, \\ \psi_{(0,1)}, \psi_{(0,2)}, \\ \alpha_{(0,1)}, \alpha_{(0,2)} \end{cases}$$
 "Time, Relative Position, and Weight"

Dynamic Model $\mathbf{x} = \mathbf{F}(\mathbf{v}, \mathbf{u})$ "Generalized Rigid Body Dynamics" $r(\mathbf{v}, k)$ "Prior Motion Information"

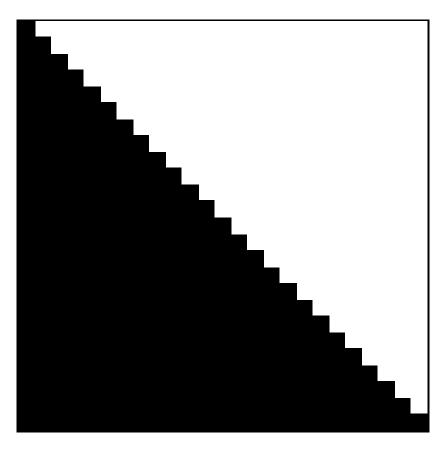
Functional Measure $s_0(\mathbf{u}, \mathbf{x}, (a, b)) = (\mathbf{x}(\mathbf{t}_b) - \mathbf{x}(\mathbf{t}_a) - \mathbf{\psi}_{(a,b)})^2 \alpha_{(a,b)}$ "Relative Trajectory Measure"

Optimization Problem
$$\mathbf{v}^* = \operatorname*{argmin}_{\mathbf{v} \in \mathbb{V}} \left\{ \sum_{k \in \mathbb{K}} r(\mathbf{v}, k) + \sum_{(a,b) \in \mathbb{A}} s_0(\mathbf{u}, \mathbf{x}, (a,b)) \right\}$$
 "Weighted Least Squares with Prior"

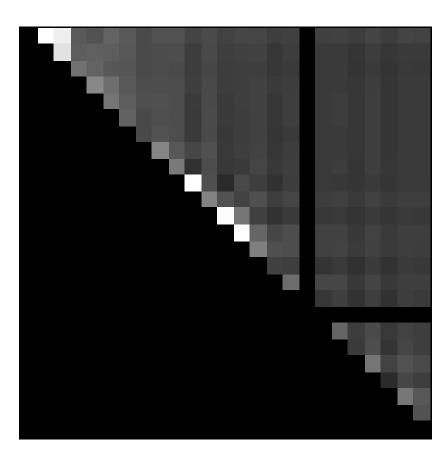
Framework Variables and Functions

$\mathbb R$	real numbers	
$\mathbb{Z}_{\scriptscriptstyle +}$	non-negative integers	
\mathbb{S}^3	quaternion rotation group	
$\mathbb{K} = \{k : k \in \mathbb{Z}_+, k \le K\}$	discrete time index	
$\mathbb{T} = \left\{ t : t \in \mathbb{R}, t_0 \le t \le t_K \right\}$	continuous time index	
$\mathbb{M} = \{ m : m \in \mathbb{Z}_+, m < M \}$	measure index	
$\mathbb{A} = \left\{ (a,b) : a,b \in \mathbb{Z}_+, \\ A_m \le a \le b \le B_m, m \in \mathbb{M} \right\}$	ordered pair of data nodes	
$\mathbb{U} = \{\mathbf{u} : \mathbb{Z}_+ \to \{0,1\}\}$	raw sensor data	
$\mathbb{V}=\left\{ \mathbf{v}:\mathbb{K} ightarrow\mathbb{Z}_{+}^{D_{k}},k\in\mathbb{K} ight\}$	dynamic model parameters	
$\mathbb{X} = \left\{ \mathbf{x} : \mathbb{T} \to \mathbb{R}^3 \times \mathbb{S}^3 \right\}$	continuous body trajectory	
$\mathbf{F}: \mathbb{V} imes \mathbb{U} o \mathbb{X}$	functional dynamic model	
$\mathbf{p}:\mathbb{T} \to \mathbb{R}^3$	body position	
$\mathbf{q}:\mathbb{T} o\mathbb{S}^3$	body orientation	
$r: \mathbb{V} \times \mathbb{K} \to \mathbb{R}$	prior measure	
$s: \mathbb{M} \times \mathbb{U} \times \mathbb{X} \times \mathbb{A} \to \mathbb{R}$	conditional measure	

Visualizing the Problem Structure



Adjacency Matrix



Cost Matrix



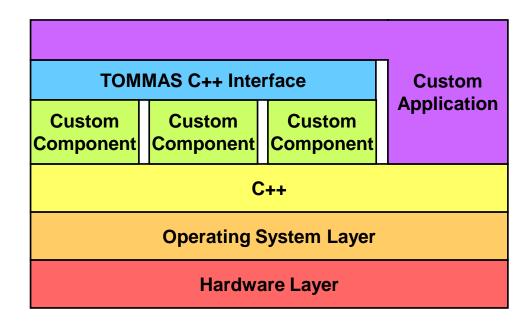
Absolute Measure: "I am near McDonalds"

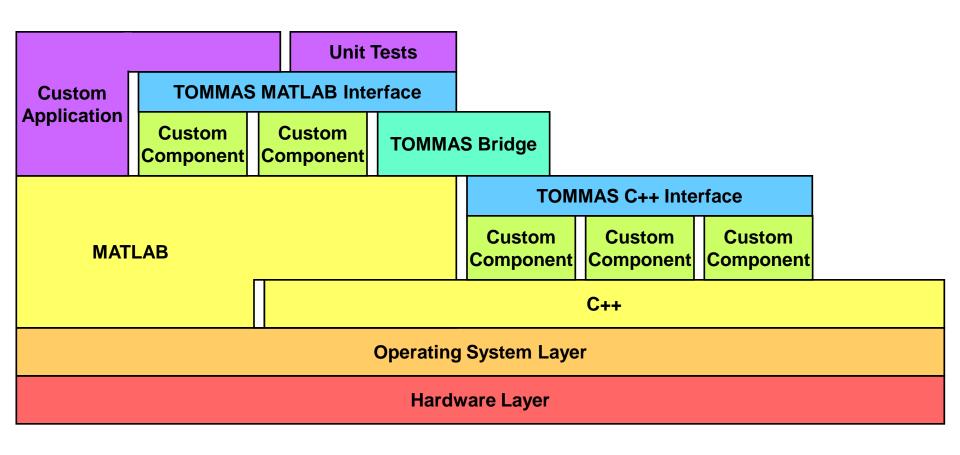
"Now I see a large Citgo sign and Soverign Bank..."



Software Licensing and Distribution

- Goals
 - Enable collaboration with universities and corporations
 - Encourage open and closed source development
- Policy for optimization framework and demo subsystems
 - Hosted at http://code.google.com/p/functionalnavigation/
 - License: BSD
 - Open source? YES
 - Copyleft for derivative works? NO
 - Allow linked code with different licenses? YES
 - Restrict use of owner's name by others? YES
- Policy for proprietary subsystems developed by SSCI
 - Hosted at https://svn.ssci.com/repos/functionalnavigation
 - License: SBIR Data Rights
 - All rights reserved for 5 years
 - Contact SSCI with commercial inquiries





How to Implement a TOMMAS Component

- Review the paper in JNC 2011:
 - "A General Framework for Trajectory Optimization with Respect to Multiple Measures"
- Navigate to the online repository
 - http://code.google.com/p/functionalnavigation
- Review the Wiki pages
- Download the TOMMAS framework code
- Refer to the internal code documentation in the C++ header files located in the "trunk/+tom" and "trunk/+antbed" directories
- Use the components in "trunk/components" as templates
 - Algorithm library includes: optical flow, bundle adjustment, EKF, gradient descent, genetic algorithm, simplex, SLAM methods, generic dynamics, and flight dynamics