## Characterization of Measures

We present novel techniques for characterizing combinations of sensors and algorithms given real or simulated sensor data from a platform with a known trajectory.

By design, our definition of a trajectory measure conceals the details of its implementation behind an opaque interface. Therefore, existing sensor-specific characterizations cannot be applied to them. This highlights the need for new methods to characterize generalized trajectory measures, such that meaningful scores are generated in categories relevant to navigation.

A TOMMAS measure is derived from the mathematical foundations of measure theory: In our formulation, the set of all possible data values that a sensor can produce constitutes a σ-*algebra*. A measure assigns a non-negative real number to any subset of the data, commonly interpreted as the size, length, or volume of the subset. The measure of the union of any two disjoint elements is the sum of the measures of the individual elements, and the measure of the empty set is zero. If the measure of the whole set is one, then it is a probability measure (not required for TOMMAS measures).

We propose that measures that assign increasing cost to increasing inconsistency between the data and the given trajectory.

This analysis will help a system designer to create an overall objective function for navigation, based on a combination of sensors and algorithms that together meet the requirements of a given mission.

It is important to distinguish between a trajectory measure and its characterization. In order to characterize trajectory measures, a scorecard will be presented as a table with rows corresponding to algorithms and columns corresponding to datasets. A measure will receive a score for each of several characteristics based on each sample of data from our industry partners. Scores can only be derived from data sets that are accompanied by ground truth.

A relevant example of a scorecard can be seen on the Middlebury stereo vision evaluation website[1]. It offers a table with rows corresponding to algorithms and columns corresponding to datasets. Several datasets are provided with ground truth, from which to characterize measures related to stereo depth reconstruction. Each data set has only a few data elements, which in this case are stereo image pairs.

We plan to construct a similar scorecard. A measure will receive a score for each of several characteristics based on samples of data from the public domain and from AFRL. Scores will be computed by perturbing the ground truth trajectory and evaluating costs. Characteristics of interest include:

**Cost** – The smoothed value of the cost function in the vicinity of ground truth.



Where  is the final cost produced by the measure when passed , the ground truth provided by the data container, and data .

**Jacobian** – Sensitivity of the cost function in the vicinity of ground truth.

**Hessian** – This is the inverse of covariance in the case of normally-distributed measurement error and it is related to Circular Error Probable (CEP) by a simple transformation. It is computed by second order perturbations of the cost functional in the vicinity of ground truth. We also compute the Eigen vectors, Eigen values, and Eigen value ratios of this matrix.

**Granularity** – Distance in meters or radians until cost increases, similar to dilution of precision.

 such that 

Where  is the minimum value necessary to produce a different cost.

**Monotonicity** – Distance in meters or radians until cost begins to decrease.

**Computation** – Equivalent number of floating point operations required to compute cost.

**References**

1. Middlebury College. *Stereo Vision Research Page*. http://vision.middlebury.edu/stereo/eval/