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Ivan Kadar
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Contents

ix Conference Committee

xiii *Invited Panel Discussion: Issues and Challenges in Performance Assessment of Multitarget Tracking Algorithms with Applications to Real-World Problems*
I. Kadar, Interlink Systems Sciences, Inc. (USA); E. Blasch, Air Force Research Lab. (USA); C. Yang, Sigtem Technology, Inc. (USA); O. E. Drummond, CyberRnD, Inc. (USA) and Consulting Engineer (USA); W. D. Blair, Georgia Institute of Technology (USA); G. Chen, DCM Research Resources, LLC (USA); L. Bai, Temple Univ. (USA); C.-Y. Chong, BAE Systems (USA); X. R. Li, Univ. of New Orleans (USA); R. Mahler, Lockheed Martin MS2 Tactical Systems (USA); T. Kirubarajan, McMaster Univ. (Canada)

MULTISENSOR FUSION, MULTITARGET TRACKING, AND RESOURCE MANAGEMENT I

- 6968 02 **Some interesting observations regarding the initialization of unscented and extended Kalman filters** [6968-01]
A. J. Noushin, F. E. Daum, Raytheon Integrated Defense Systems (USA)
- 6968 04 **A simple algorithm for sensor fusion using spatial voting (unsupervised object grouping)** [6968-68]
H. M. Jaenisch, Alabama A&M Univ. (USA) and Licht Strahl Engineering Inc. (USA); N. G. Albritton, Amtec Corp. (USA); J. W. Handley, Licht Strahl Engineering Inc. (USA) and Amtec Corp. (USA); R. B. Burnett, R. W. Caspers, W. P. Albritton, Jr., Amtec Corp. (USA)
- 6968 05 **A particle-filtering approach to convoy tracking in the midst of civilian traffic** [6968-03]
E. Pollard, B. Pannetier, ONERA (France); M. Rombaut, GIPSA Lab. (France)
- 6968 06 **Long-term ground movement prediction by Monte Carlo simulation** [6968-04]
M. J. Carlotto, General Dynamics Advanced Information Systems (USA)
- 6968 07 **Gaussian mixture probability hypothesis density smoothing with multistatic sonar** [6968-05]
N. Nandakumaran, R. Tharmarasa, McMaster Univ. (Canada); T. Lang, General Dynamics Canada (Canada); T. Kirubarajan, McMaster Univ. (Canada)
- 6968 08 **Estimating target range-Doppler image slope for maneuver indication** [6968-06]
C. Yang, Sigtem Technology, Inc. (USA); E. Blasch, Air Force Research Lab. (USA)
- 6968 09 **Effect of sensor bias on space-based bearing-only tracker** [6968-07]
T. M. Clemons III, K. C. Chang, George Mason Univ. (USA)

MULTISENSOR FUSION, MULTITARGET TRACKING, AND RESOURCE MANAGEMENT II

- 6968 0A **Improving automatic cooperation between UAVs through co-evolution** [6968-08]
J. F. Smith III, Naval Research Lab. (USA)

- 6968 OD **Evaluation of an information-based sensor management system** [6968-11]
J. Malachowski, K. J. Hintz, George Mason Univ. (USA)
- 6968 OE **Collaborative distributed sensor management and information exchange flow control for multitarget tracking using Markov decision processes** [6968-12]
D. Akselrod, T. Kirubarajan, McMaster Univ. (Canada)

ASSISTED TARGET RECOGNITION (ATR) I

- 6968 OF **Experimental feature-based SAR ATR performance evaluation under different operational conditions** [6968-13]
Y. Chen, Intelligent Automation, Inc. (USA); E. Blasch, Air Force Research Lab. (USA); H. Chen, Univ. of New Orleans (USA); T. Qian, Intelligent Automation, Inc. (USA); G. Chen, DCM Research Resources LLC (USA)
- 6968 OG **Detecting missile-like flying target from a distance in sequence images** [6968-14]
X. Li, G. Chen, DCM Research Resources LLC (USA); E. Blasch, K. Pham, Air Force Research Lab. (USA)
- 6968 OH **Generation of efficient 2D templates from 3D multisensor data for correlation-based target tracking** [6968-15]
C. Witte, W. Armbruster, K. Jäger, M. Hebel, Research Institute for Optronics and Pattern Recognition (Germany)
- 6968 OI **An approach for evaluating assisted target detection technology** [6968-16]
J. M. Irvine, National Geospatial-Intelligence Agency (USA); J. Leonard, Air Force Research Lab. (USA); P. Doucette, A. Martin, National Geospatial-Intelligence Agency (USA)

ASSISTED TARGET RECOGNITION (ATR) II

- 6968 OJ **On the limits of target recognition in the presence of atmospheric effects** [6968-17]
X. Chen, N. A. Schmid, West Virginia Univ. (USA)
- 6968 OK **A distributed automatic target recognition system using multiple low resolution sensors** [6968-18]
Z. Yue, P. Lakshmi Narasimha, P. Topiwala, FastVDO Inc. (USA)
- 6968 OL **Multi-viewpoint image fusion for urban sensing applications** [6968-19]
F. Ahmad, M. G. Amin, Villanova Univ. (USA)
- 6968 OM **Virtual simulation tools for artillery** [6968-20]
P. Gozard, E. Bret, DGA/DET/ETBS (France); T. Cathala, OKTAL Synthetic Environment (France)

MULTISENSOR FUSION METHODOLOGIES AND APPLICATIONS I

- 6968 ON **Multitarget-moment filters for nonstandard measurement models** [6968-21]
R. Mahler, Lockheed Martin MS2 Tactical Systems (USA)

6968 0O **Joint search and sensor management for geosynchronous satellites** [6968-22]
A. Zatezalo, A. El-Fallah, Scientific Systems Co., Inc. (USA); R. Mahler, Lockheed Martin Tactical Defense Systems (USA); R. K. Mehra, Scientific Systems Co., Inc. (USA); K. Pham, Air Force Research Lab. (USA)

6968 0P **Dynamic sensor management of dispersed and disparate sensors for tracking resident space objects** [6968-23]
A. El-Fallah, A. Zatezalo, Scientific Systems Co., Inc. (USA); R. Mahler, Lockheed Martin Tactical Defense Systems (USA); R. K. Mehra, Scientific Systems Co., Inc. (USA); D. Donatelli, Air Force Research Lab. (USA)

MULTISENSOR FUSION METHODOLOGIES AND APPLICATIONS II

6968 0Q **An initial investigation into incorporating human reports into a road-constrained random set tracker** [6968-31]
D. W. Winters, J. B. Witkoskie, W. S. Kuklinski, The MITRE Corp. (USA)

6968 0R **Service-based extensions to the JDL fusion model** [6968-25]
R. T. Antony, Science Applications International Corp. (USA); J. A. Karakowski, U.S. Army RDEC (USA)

6968 0S **Handling target obscuration through Markov chain observations** [6968-26]
M. A. Kouritzin, B. Wu, Univ. of Alberta (Canada)

MULTISENSOR FUSION METHODOLOGIES AND APPLICATIONS III

6968 0T **Statistical, biological, and categorical sensor fusion: an integrated methodology** [6968-27]
J. Bonick, C. Marshall, U.S. Army RDECOM CERDEC NVESD (USA)

6968 0U **A confidence paradigm for classification systems** [6968-28]
N. J. Leap, K. W. Bauer, Jr., Air Force Institute of Technology (USA)

MULTISENSOR FUSION METHODOLOGIES AND APPLICATIONS IV

6968 0X **Structured pedigree information for distributed fusion systems** [6968-24]
P. O. Arambel, BAE Systems (USA)

6968 0Y **Analytical performance evaluation for autonomous sensor fusion** [6968-32]
K. C. Chang, George Mason Univ. (USA)

6968 0Z **Convergence study of message passing in arbitrary continuous Bayesian networks** [6968-33]
W. Sun, K. C. Chang, George Mason Univ. (USA)

6968 10 **Algebra of Dempster-Shafer evidence accumulation** [6968-34]
R. H. Enders, A. K. Brodzik, M. R. Pellegrini, The MITRE Corp. (USA)

MULTISENSOR FUSION METHODOLOGIES AND APPLICATIONS V

- 6968 11 **Incorporation of indirect evidence into an evidence accrual technique for higher level data fusion** [6968-36]
S. C. Stubberud, Rockwell-Collins (USA); K. A. Kramer, Univ. of San Diego (USA)
- 6968 12 **Results from levels 2/3 fusion implementations: issues, challenges, retrospectives, and perspectives for the future an annotated perspective (Invited Paper)** [6968-37]
I. Kadar, Interlink Systems Sciences, Inc. (USA); E. Bosse, Defence R&D Canada, Valcartier (Canada); J. Salerno, Air Force Research Lab. (USA); D. A. Lambert, Defence Science and Technology Organisation (Australia); S. Das, Charles River Analytics, Inc. (USA); E. H. Ruspini, SRI International (USA); B. J. Rhodes, BAE Systems (USA); J. Biermann, FGAN-FKIE (Germany)
- 6968 13 **A collaborative eye to the future** [6968-38]
K. A. Greene, T. Goan, E. R. Creswick, Stottler-Henke Associates, Inc. (USA)

SIGNAL AND IMAGE PROCESSING I

- 6968 14 **Efficient super-resolution image reconstruction applied to surveillance video captured by small unmanned aircraft systems** [6968-39]
Q. He, Mississippi Valley State Univ. (USA); R. R. Schultz, Univ. of North Dakota (USA); C.-H. H. Chu, Univ. of Louisiana at Lafayette (USA)
- 6968 15 **Super-resolution image reconstruction from UAS surveillance video through affine invariant interest point-based motion estimation** [6968-40]
Q. He, Mississippi Valley State Univ. (USA); R. R. Schultz, A. Camargo, Y. Wang, F. Martel, Univ. of North Dakota (USA)
- 6968 16 **A smart iterative algorithm for multisensor image registration** [6968-41]
S. DelMarco, V. Tom, H. Webb, BAE Systems (USA)
- 6968 17 **3D organization of 2D urban imagery** [6968-42]
P. Cho, Massachusetts Institute of Technology (USA)
- 6968 18 **Fusing images and maps** [6968-43]
M. J. Carlotto, General Dynamics Advanced Information System (USA)
- 6968 19 **An investigation of image fusion algorithms using a visual performance-based image evaluation methodology** [6968-44]
K. E. Neriani, Consortium Research Fellows Program (USA) and Air Force Research Lab. (USA); A. R. Pinkus, Air Force Research Lab. (USA); D. W. Dommert, General Dynamics-Advanced Information Engineering Systems (USA)
- 6968 1A **Compressed sensing technique for high-resolution radar imaging** [6968-45]
Y.-S. Yoon, M. G. Amin, Villanova Univ. (USA)
- 6968 1C **Fast algorithms for video target detection and tracking** [6968-47]
C. Li, J. Si, Arizona State Univ. (USA); G. P. Abousleman, General Dynamics C4 Systems (USA)

- 6968 1D **Interval least-squares filtering with applications to video target tracking** [6968-48]
B. Li, C. Li, J. Si, Arizona State Univ. (USA); G. Abousleman, General Dynamics C4 Systems (USA)

SIGNAL AND IMAGE PROCESSING II

- 6968 1E **Frustrated polarization fiber Sagnac interferometer displacement sensor** [6968-50]
A. D. McAulay, J. Wang, Lehigh Univ. (USA)
- 6968 1F **On modeling sea clutter by diffusive models** [6968-51]
J. Hu, Univ. of Florida (USA); W. Tung, Purdue Univ. (USA); J. Gao, Univ. of Florida (USA); R. S. Lynch, Naval Undersea Warfare Ctr. (USA); G. Chen, DCM Research Resources LLC (USA)
- 6968 1G **On modeling sea clutter by noisy chaotic dynamics** [6968-52]
W. Tung, Purdue Univ. (USA); J. Hu, J. Gao, Univ. of Florida (USA); R. S. Lynch, Naval Undersea Warfare Ctr. (USA); G. Chen, DCM Research Resources LLC (USA)
- 6968 1J **Large spot size laser vibrometry insensitivity occurs in 1-D vibrations only** [6968-58]
M. C. Kobold, General Dynamics-Advanced Information Systems (USA)

SIGNAL AND IMAGE PROCESSING III

- 6968 1K **The use of interferoceiver for the prevention of fratricide in missile defense** [6968-55]
M.-C. Li, Liceimer (USA)
- 6968 1M **Empirical performance of the spectral independent morphological adaptive classifier** [6968-57]
J. B. Montgomery, C. T. Montgomery, M&M Aviation (USA); R. B. Sanderson, J. F. McCalmont, Air Force Research Lab. (USA)
- 6968 1N **Comparison of theoretical and empirical statistics of wind measurements with validation lidar (VALIDAR)** [6968-59]
J. Y. Beyon, California State Univ., Los Angeles (USA); G. J. Koch, M. J. Kavaya, NASA Langley Research Ctr. (USA); M. Sahota, California State Univ., Los Angeles (USA)

POSTER SESSION

- 6968 1O **A real-time geographical information exchange system with PDA** [6968-60]
J. He, X. Zhang, B. Sun, Beijing Normal Univ. (China)
- 6968 1P **Object recognition in infrared image sequences using scale invariant feature transform** [6968-61]
C. Park, K. Bae, Samsung Thales Co., Ltd. (South Korea); J.-H. Jung, Korea Advanced Institute of Science and Technology (South Korea)

- 6968 1Q **Image fusion in infrared image and visual image using normalized mutual information** [6968-62]
C. Park, K. Bae, S. Choi, Samsung Thales Co., Ltd. (South Korea); J.-H. Jung, Korea Advanced Institute of Science and Technology (South Korea)
- 6968 1R **Dynamic stimulus enhancement with Gabor-based filtered images** [6968-63]
A. R. Pinkus, Air Force Research Lab. (USA); M. J. Poteet, Consortium Research Fellows Program (USA); A. J. Pantle, Miami Univ. (USA)
- 6968 1S **Correlating military operators' visual demands with multi-spectral image fusion** [6968-64]
G. L. Martinsen, J. S. Hosket, A. R. Pinkus, Air Force Research Lab. (USA)
- 6968 1U **Multisensory data exploitation using advanced image fusion and adaptive colorization** [6968-66]
Y. Zheng, K. Agyepong, O. Kuljaca, Alcorn State Univ. (USA)
- 6968 1V **Multi-mode sensor processing on a dynamically reconfigurable massively parallel processor array** [6968-67]
P. Chen, M. Butts, B. Budlong, P. Wasson, Ambric, Inc. (USA)

Author Index

Conference Committee

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Session Chairs

Multisensor Fusion, Multitarget Tracking, and Resource Management I
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)
Thiagalingam Kirubarajan, McMaster University (Canada)
Kenneth J. Hintz, George Mason University (USA)

Multisensor Fusion, Multitarget Tracking, and Resource Management II
Kenneth J. Hintz, George Mason University (USA)
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)

Assisted Target Recognition (ATR) I
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)
Kenneth J. Hintz, George Mason University (USA)

Assisted Target Recognition (ATR) II
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)
Kenneth J. Hintz, George Mason University (USA)

Multisensor Fusion Methodologies and Applications I
Ronald P. Mahler, Lockheed Martin Corporation (USA)

Multisensor Fusion Methodologies and Applications II
Ronald P. Mahler, Lockheed Martin Corporation (USA)

Multisensor Fusion Methodologies and Applications III
Michael L. Hinman, Air Force Research Laboratory (USA)
Chee-Yee Chong, BAE Systems Advanced Information Technologies
(USA)
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)

Multisensor Fusion Methodologies and Applications IV
Michael L. Hinman, Air Force Research Laboratory (USA)
Chee-Yee Chong, BAE Systems Advanced Information Technologies
(USA)
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)

Multisensor Fusion Methodologies and Applications V
Michael L. Hinman, Air Force Research Laboratory (USA)
Ivan Kadar, Interlink Systems Sciences, Inc. (USA)

Signal and Image Processing I
Lynne L. Grewe, California State University/East Bay (USA)
Alastair D. McAulay, Lehigh University (USA)
Mark G. Alford, Air Force Research Laboratory (USA)

Signal and Image Processing II
Alastair D. McAulay, Lehigh University (USA)
Lynne L. Grewe, California State University/East Bay (USA)
Mark G. Alford, Air Force Research Laboratory (USA)

Signal and Image Processing III
Mark G. Alford, Air Force Research Laboratory (USA)
Lynne L. Grewe, California State University/East Bay (USA)
Alastair D. McAulay, Lehigh University (USA)

Invited Panel Discussion
Issues and Challenges in Performance Assessment
of Multitarget Tracking Algorithms with
Applications to Real-World Problems

Organizer

Ivan Kadar, Interlink Systems Sciences, Inc.

Moderators

Ivan Kadar, Interlink Systems Sciences, Inc.

Dale Blair, Georgia Tech Research Institute

March 17, 2008

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"Signal Processing, Sensor Fusion and Target Recognition XVII"

Orlando, FL March 16-20, 2008

Invited Panel Discussion

Participants:

Dr. Dale Blair, Georgia Tech. Research Institute

Dr. Erik P. Blasch, Air Force Research Lab.

Dr. Chee-Yee Chong, BAE Systems

Dr. Oliver Drummond, CyberRnD and Consulting Engineer

Dr. Ivan Kadar, Interlink Systems Sciences, Inc.

Professor Thiagalingam Kirubarajan, McMaster Univ.

Professor X. Rong Li, Univ. of New Orleans

Dr. Ronald P. S. Mahler, Lockheed Martin MST2 Tactical Systems

Invited Panel Discussion

Topics

"Issues and Challenges in Model-Based Performance Assessment of Multi-Target Trackers" Dr. Ivan Kadar, Interlink Systems Sciences, Inc.

"Target-to-Track Assignment in Performance Evaluation of Multiple Target Tracking" Dr. Oliver Drummond P.E., CyberRnD, Inc., and Consulting Engineer

"Modeling and Simulation: Key to Effective Performance Assessment of Multiple Tracking Algorithms " Dr. Dale Blair, Georgia Tech Research Institute.

"Performance Assessment of Multitarget Tracking Algorithms in the Real World" Dr. Erik P. Blasch, Air Force Research Lab., Dr.Chun Yang, Sigtem Technology, Inc., Dr.Genshe Chen, DCM Research Resources, LLC, Dr.Ivan Kadar, Interlink Systems Sciences, Inc., and Professor Li Bai, Temple University

Invited Panel Discussion

Topics

"Consumer Reports Approach for Assessing Multi-target Trackers" Dr. Chee-Yee Chong, BAE Systems

"Challenges and Recent Advances in Estimation Performance Evaluation" Professor X. Rong Li, Univ. of New Orleans

"Global Performance MOEs for Multitarget Tracking" Dr. Ronald P. S. Mahler, Lockheed Martin MS2 Tactical Systems

"How Useful Are Theoretical Bounds in the Real World" Professor Thiagalingam Kirubarajan, McMaster Univ. (Canada)

Issues and challenges in model-based performance assessment of multi-target trackers

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ABSTRACT

This paper presents a basic look at the issues and challenges in assessing the performance of multi-target trackers using model-based simulation/prediction/correction methods. Issues of realistic modeling of “real data” including effects of target densities and target behaviors, environment (clutter) and sensor models are highlighted. The use of robust preprocessing is proposed to eliminate measurement outliers. The performance assessment consists of decomposing the tracker into association and state estimation elements, and comparing the performance of the individual components to the tracking system performance, with both simulated model-based and with real data. The potential of either post-hoc, and/or on-line performance-monitoring methods of the tracker under test are proposed along with corrective feedback in order to improve tracking system performance.

Keywords: Predictive/corrective performance assessment, multi-target tracking algorithms

1. INTRODUCTION

This paper presents a basic and succinct view of issues and challenges in assessing the performance of multi-target trackers using model-based simulation/prediction/correction methods. Issues of realistic modeling of “real data” including effects of target densities and target behaviors, environment (clutter) and sensor models are highlighted. The use of robust preprocessing is proposed to eliminate measurement outliers. Robust-preprocessing removes outliers that persist as propagating errors through the tracker, but does not mitigate the effects of non-Gaussian measurement noise caused by clutter and the multiplicative noise effects of multipath. The proposed performance assessment scheme consists of decomposing the tracker into association and prediction/state estimation elements, and comparing (1) the performance of the individual components over time, (2) tracking system performance over time, and (3) individual-to-system performance, with both simulated model-based and real data. The potential of either post-hoc, and/or on-line methods of monitoring the performance of the tracker under test are proposed along with corrective feedback in order to improve tracking system performance, sensor [2] and environmental models.

The paper is organized as follows: we first depict methods of performance assessment, followed by the above proposed approach, and subsequently discuss models, methods, issues, and challenges in addressing the complexity of the problem. As system-level performance is challenged by increased complexity (e.g. distributed processing), it is ever important to understand the issues and methods in developing a comprehensive performance evaluation plan.

2. MODEL-BASED PERFORMANCE ASSESSMENT: ISSUES AND CHALLENGES

It is well known that there are two ways to predict an estimator kinematic performance [1], one is to use a model-based simulation approach, and other is to use an analytical approach. The *model-based approach*, both utilizes and combines environment (clutter), target behavior/characteristics, detection and sensor models [2], and uses a time series of simulated or real measurements to form a state estimate, which is compared with respect to a measure-of-merit [3] or ground truth. An *analytical model*, if feasible, would rely on a steady state filter model to predict the performance of the state estimate, given target, environment and sensor models. Furthermore, the analytical model, in general, assumes stationary target and sensor model parameters [2], and would not allow taking into account time dependence inherent in a tracking system. Note that the above discussion assumed perfect measurement-to-track association. To account for uncertainty in measurement-to-track association, an optimal association metric in terms of probability of correct association, P_{CA} , can be used to provide a probabilistic bound on the achievable association performance for a given scenario, as proposed by [4]. The probability of correct association is given by, $P_{CA} = e^{-\beta}$, where, β is the normalized target density defined as the average number of objects in a one-sigma region of the measurement space, D_m , and β is

given by, $\beta = D_m |R|^{1/2}$, where R is the measurement error covariance [4]. Typical association algorithms can consist of nearest neighbor, Jonker-Volgenant-Castonon (JVC) assignment, multi-frame association or multiple hypotheses tracking [5].

It is also well known [5, 6, 7], that trackers are intrinsically nonlinear, (even in the case of a linearized model, depending on the type of measurements and parametric excursions) and the measurement error sources can become potentially non-Gaussian, and also can be contaminated with outliers. In spite of this, algorithms are usually designed under the usual Additive White Gaussian Noise (AWGN) assumption [5]. In addition, with many maneuvering or crossing and merge-and-split targets present, even under AWGN measurement noise conditions, the tracker may not be able to model all possible target dynamics, and the resultant distribution of the innovations sequence may not necessarily be AWG distributed [5]. While the later condition can be used to identify target maneuvers [5], it will also degrade tracker performance, and thus can become a metric [8] to be monitored for performance degradation as described in Section 3. In order to assess the efficacy of the models inherent in a given tracker, [9] proposed the maneuvering index, λ , as a measure to determine whether a single model or multiple interacting models are needed, depending of the value of λ , [5, 9] for best performance. The target maneuvering index, λ , is given by $\lambda = \sigma_v T^2 / \sigma_w$, where σ_v is the process noise standard deviation, T is the revisit interval, and σ_w is the measurement noise standard deviation.

Therefore, depending on computation of specific range of values of λ [9] for a given tracker/model, will give the modeler *a-priori* knowledge what performance to expect under certain stressing maneuvering target conditions before testing and, along with the computation of P_{CA} , aid the predictive and corrective performance assessment method discussed below.

3. A MODEL-BASED PREDICTIVE AND CORRECTIVE-FEEDBACK METHOD

Given the above description of the complex problem setting, the question arises how to evaluate tracker performance, based on performance goals, performance prediction (tracker model) and ground truth, especially since models may not be able to account for the effects of nonlinearities present in trackers. Figure 1 depicts a model-based predictive/corrective approach, consisting of both post-hoc (forensic) assessment and/or an on-line monitoring corrective feedback concept for performance assessment and enhancement.

Figure 1. A model-based predictive and corrective performance assessment concept

In order to minimize potential nonlinear effects on performance due measurement noise outliers, the measurements are censored by robust nonparametric methods, such as Tukey's method of Hinges [8, 10], as indicated in Fig. 1. The

robustized measurements serve as inputs to both the tracker under test, and to the ideal performance model of the tracker. Of course, there are many other error sources remaining, such as the effects of non-Gaussian measurement noise, and large parameter excursions in measurements, etc.

Performance metrics can be either *absolute*, with respect to ground truth, or using a substitution method to calibrate “predicted (i.e., model) performance” with respect to ground truth, or *relative* with respect to goals, refer to Fig. 1, as established by the scenario, by using selected families of tracking/estimation metrics as described in [5, 6, 7, 11].

In order to optimize tracker performance under test, two methods of corrective feedback are considered, refer to Fig. 1: (1) a *post-hoc* (forensic) analysis of tracker performance by monitoring the state estimates, and the distribution of the innovations sequence [8], (2) using *on-line* assessment of the same parameters as in (1), but providing on-line feedback to both the tracker dynamic models and gating to improve performance, as needed. In order to evaluate the tracker components, consisting of association and state estimation, a single target scenario or widely separated targets can be used to remove the effects of association, and to test the estimation component with a range of target motions/dynamics, sensor errors and update rates [7]. In an analogous manner, the association component can be tested with non-maneuvering targets. It should be noted, that while not explicitly stated, the above method could be applied to evaluate families of trackers, e.g., using linearized and/or extended Kalman filters, and interacting multiple models, utilizing association algorithms such as nearest neighbor, JVC, multiple hypotheses tracking or multi-frame association [5].

4. CONCLUSIONS

This paper presented a basic and comprehensive view of issues and challenges in assessing the performance of multi-target trackers using model-based simulation/prediction/correction methods. Issues of realistic modeling of “real data” including effects of target densities and target behaviors, environment (clutter) and sensor models were highlighted. The use of robust preprocessing of measurements was proposed to eliminate measurement noise produced outliers. The proposed performance assessment consisted of decomposing the tracker into association and state estimation elements, in order compare the performance of the individual tracker components, and of the tracking system performance, with both simulated model-based and with real data. The potential of either post-hoc, and/or on-line methods of monitoring the performance of the tracker under test were proposed along with corrective feedback in order to improve tracking system performance. The next step is to test the efficacy of the proposed conceptual method first in a simulation testbed, as an extension to [8], and subsequently in a benchmark like environment [7] with real data.

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Target-to-Track Assignment in Performance Evaluation of Multiple Target Tracking

Excerpts From
Multiple Target Tracking Lecture Notes

SPIE Panel on Issues and Challenges in Performance Assessment of
Multitarget Tracking Algorithms with Applications to Real-World Problems
17 March 2008

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Some Observations On Target Tracking (1 of 2)

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- Each of the Four Classes of Tracking Problems Poses Different Algorithm Development Issues, Therefore This Presentation Concentrates on Only One Class of Tracking, Namely, Tracking of Small Targets Using Multiple-Target Tracking Methods.
- Because Optimal Tracking Methods Are Too Complex to Be Practical, Suboptimal (Ad Hoc) Algorithms Are Typically Devised That Take Advantage of the Particular Targets, Sensors, and Related Conditions of the System for Which the Tracker Is Designed.
 - ♦ In algorithm development, the major trade is between tracking performance and the processor loading plus communications loading, if applicable
 - ♦ Note that the {Kalman} filter equations are not very difficult to implement; it is the selection of the type of filter, structure of the mathematical model and its parameter values used to design the filter that require extensive knowledge and experience. The data association function is similar.

Sp2007n01E.v1.ppt Page 2

Some Observations On Target Tracking (2 of 2)

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- A Fundamental Characteristic of Small Target Tracking Is That It Involves Both Discrete and Continuous Random Variables or Parameters.
 - ♦ Because of the resulting complex nature of the estimation errors, multiple target-tracking performance evaluation and prediction are not amenable to analysis.
 - ♦ A high fidelity Monte Carlo simulation plus field testing are a necessary part of most tracking algorithm development efforts.
 - ♦ Some simulation results appear initially to be counterintuitive.
 - ♦ Algorithm development of the trackers for a system is typically an experimental and recursive process.
 - ♦ Tracking exhibits properties significantly different from signal processing; in addition to Type 1 and Type 2 errors, tracking exhibits Type 3 errors, that is a combination of both missed and false tracks.

Sp2007n01E.v1.ppt Page 3

Misassociations Complicate Tracker Performance Evaluation

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- Misassociations and Target Maneuvers Can Create:
 - ♦ Extra (False) Tracks:
 - Redundant (Duplicate) Tracks
 - Spurious Tracks, Including Valid Tracks That Become Invalid (Get "Lost")
 - ♦ Missed Targets (Missed Tracks)
 - ♦ Track Swaps/Switches (Track Changes Target It Is Following)

How to Identify Them?

- Misassociations Can Create Ambiguity About Which Track Is Following A Specific Target, If Any.

Need to Decide Which Track Goes With Each Target, If Any?

Sp2007n01E.v1.ppt Page 4

Performance Evaluation Methodology

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- Presentation Concentrates On Assignment Of Targets To Tracks
- Assume Task Is To Fairly Compare The Performance Of Two Or More Trackers (or Two Versions of a Tracker) Under Challenging Conditions And The Trackers Are Already Developed.
- Due To Nature Of Problem, Can Expect That There Is No One Methodology On Which Everyone Will Agree!
- May Need To Use More Than One Methodology
- For Simplicity Of Presentation, Assume NO Track Intentionally Represents Multiple Targets
- Define All Tracks That Are Not Valid As Extra (False) Tracks:
 - ♦ $\# \text{Tracks} = \# \text{Valid Tracks} + \# \text{Extra Tracks}$
 - ♦ $\# \text{Targets} = \# \text{Valid Tracks} + \# \text{Missed Targets, i.e., Missed Tracks}$
 - ♦ Note: Two Equations but Three Unknowns

Sp2007n01E.v1.ppt Page 5

The Two-Step Methodology

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The Emphasis of This Presentation Is on Step 1

Details of the Methodology Depend Heavily on the Purpose of the Evaluation and the Constraints

Sp2007n01E.v1.ppt Page 6

Problem: Which Target Goes With Each Track?

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Sp20070415E.vpt Page 7

What If Nearest Track Is Assigned To Each Target?

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What If Nearest Target Is Assigned To Each Track?

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"Unique" 2D-Assignment Of Track-Target Pairs

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Sp20070415E.vpt Page 10

Unique Assignment Of Targets To Tracks Using Gates

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Alternative Assignment Cost Functions

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- **Assignment Cost Based On Target "Source" Of Measurements**
 - ◆ Compute The Percentage Of The Recent Measurements (In A Moving Window) Used By The Track That Are Not Due To The Subject Target
 - ◆ Must Identify Measurements Used By Each Track And The Target That Caused Each Measurement – Might Be Computationally Complex And Invasive
 - ◆ Typically Field Tests And Some Simulations Do Not Provide Needed Data
 - ◆ May Show Unfair Preference In Favor Of Hard-Decision Trackers And Against Soft-Decision Trackers
- **Assignment Cost Based On (Statistical) Distance In State Space Using State Estimate (And Possibly Covariance Matrix Of Track)**
 - ◆ Tends To Be Fairer When Comparing Two Or More Trackers
 - ◆ For Example, Treats Soft-Decision Tracking Algorithms Fairly, Such As PDAF and JPDA Trackers and Does Not Reveal Tracker Design
 - ◆ Computation Of the Assignment Cost Is Relatively Simple
 - ◆ Can Be Computed From Field Test Data That Includes Target Truth
 - ◆ This Is The Recommended Method For Many High Fidelity Simulations

Sp20070415E.vpt Page 12

Using Track Gate Provides Meaningful Results

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- Gates Limit Permissible Assignment Cost So That Assignment Of A Target That Is Too Far From A Track Is Not Allowed
- Gates Facilitate Identification Of "Valid," Extra, and Missed Tracks
- Gates Eliminate Inappropriate Target-Track Pairs That Would Distort Some Measures Of Performance, Such As, Track Accuracy and Track Bias
- Statistical (Mahalanobis) Distance Is Based On Distance Between The Track State Estimate And The Target True State, Weighted By The Inverse Of Computed Track State Estimate Error Covariance Matrix

$$\chi^2 = [\mathbf{x} - \hat{\mathbf{x}}]^T \mathbf{P}^{-1} [\mathbf{x} - \hat{\mathbf{x}}] = \text{Statistical Distance}$$

$\mathbf{x}$ = True Target State

$\hat{\mathbf{x}}$ = Track Estimated Target State

$\mathbf{P}$ = Track Error Covariance Matrix

Sp2017HVEU.ppt Page 13

For High Fidelity Simulation Consider Using "Statistical Distance" And Gates To Uniquely Assign Targets To Tracks

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- If Reasonably Consistent Track Covariance Matrix Is Available, Assignment Cost Is Statistical (Mahalanobis) Distance Between Target And Track.
- Gates Threshold Assignment Cost To Exclude Unlikely Target-Track Pairs
- Traditional Approach Is To Use A Unique Assignment For Each Monte Carlo Run and Each Time Point of Interest But May Cause Track Swaps/Switches.

Sp2017HVEU.ppt Page 14

Alternatively, Use Track Purity in Track-to-Truth Assignment

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Sp2017HVEU.ppt Page 15

Concluding Comments

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- The Targets-to-Tracks Assignment Task in Performance Evaluation Is Complex and Similar-- but NOT the Same -- As the Tracking Data Association Function.
- The Method Selected for Assigning Targets to Tracks Will Have an Impact on the Performance Evaluation Results.
- Appropriate Selection of Both Targets-to-Tracks Assignment and Evaluation Metrics Algorithms Depend on the Purpose and Conditions of the Performance Evaluation.
- A Moderately Simple Single-Frame Assignment Approach Has Been Presented but a Multiple-Frame Assignment Approach Is Expected to Be More Effective.

{Supplemental Slides Follow}

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Four Types Of Performance Evaluation Methodologies

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- Assign Tracks to Targets at Preselected Times
 - Assignment at Each Time Independent of Assignments at Other Times
 - No Constraints on the Number or Types of Track Swaps
 - May Create Too Many Switches That Are Artifacts of This Method
- Assign at Most One Track Per Target for Entire Run
 - No Track Swaps Allowed
 - Maybe Useful for Evaluating Combat Identification
- Allow Feasible Track Swaps
 - Allow a Sequence of More Than One Track to be Assigned to a Target
 - Feasible Track Sequence Does Not Include Two Tracks That Exist at the Same Time Or Allow Overlap But Penalize for It
 - Useful for Evaluating Tracks for a Target That Are Terminated Early and Later Unknowingly Reinitiated
- Alternative Methods to Reduce Track Switches
 - Assignments at Preselected Times But "Discourage" Track Switches

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Comments on the Four Alternative Assignment Approaches

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- Improvements In Track-to-Truth Assignment Are Possible Using Methods Other Than Independent Decisions At Each Metric Sample Time Or With Short Non-Overlapping Window.
- Using Moving Window That Takes Advantage of Some Future Data Should Improve Results Relative to Independent Assignments Over Time
- MFA or MHT Should Provide Additional Improvement But With Additional Complexity.
- Optimal Method Has Been Described But Is NP Hard and Thus Complex With Many Targets.
- Careful Selection Of Assignment Cost Is Needed.

Sp2017HVEU.ppt Page 18

Performance Versus Processor Resources For Single Target Tracking After 7 Frames of Data With False Signals

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Page 19

Possible Outcomes for Signal Detection And Single Target Tracking

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- Type I Error: False Detection Or False (Extra) Track Given No Target In Region Of Interest.
- Type II Error: Missed Detection Or Missed Track Given Target In Region Of Interest.
- Type III Error: False (Extra) Track And Missed Track Given Target In Region Of Interest.

		Target In Plot	
		No	Yes
Detection	No	No Detect (Valid)	Miss (Type II Error)
	Yes	False (Type I Error)	Detect (Valid)

Signal Detection

		Target In Field of Regard	
		No	Yes
Track Provided	No	No Track (Valid)	Miss (Type II Error)
	Yes	False (Type I Error)	Provided (Valid)

Single Target Tracking

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Alternatives for Computing Distance for Assignment Costs

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- Could Include Features and Attributes or Target "Classification" in Assignment Cost
- Poor Consistency of Track Error Covariance Matrix Poses a Problem - Some Alternatives:
 - For Mahalanobis Distance Computation, Use Appropriate Precomputed Covariance Matrix
 - Use Current or Predicted Position Only Mahalanobis Distance
 - Use Position Euclidean Distance Squared:
 - Does Not Adjust for Dynamics of True Error Covariance Matrix
 - Difficult to Select Gate Threshold Value
 - Various Other Suboptimal Approaches Could Be Considered.
- Issue: If Not Use Mahalanobis Distance, How Adjust Size of Gates? Difficult to Adjust for Changes Over Time of True Error Covariance Matrix or Differences in Accuracy from Track to Track

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To Select Methodology, Need to Establish Purpose of Evaluation and Constraints

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- There Can Be a Variety of Reasons *Why* Performance Is Evaluated:
 - To Compare Multiple Trackers (or Variants of the Same Tracker) to Select the Best for an Application
 - Testing by the Tracker Developers
 - Testing by a Third Party or Buyer
 - May Testing Be Invasive and Reveal Tracker Design?
 - Will Tracker Indicate Which Measurements (or Tracklets) Each Track Uses?
 - To Diagnose Tracker Design or to Debug the Software or Improve Tracker
 - To Stress a Tracker to Explore Its Capability and Limits
 - To Establish Capability in order to Specify Requirements
- Degree of Fidelity of Simulations and Can Target Source of Measurement Be Determined With and Without UCSOs?
- Testing a Single Sensor Tracking Versus Sensor Fusion
- Monte Carlo Simulations Versus Using Real Data or Field Testing
- Testing Performance of Tracking Versus Both Tracking and Classification or Overall System Performance.

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Some Additional Comments On Performance Evaluation

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- Performance Evaluation Metrics Must Be Customized To Suit Your System. Therefore Some Experimentation With Alternative Performance Evaluation Methods And Metrics Should Be Planned.
- To Enhance Testing Of The Potential For Spurious Track Generation, Consider Including A Scenario Without Targets (Or Time Periods Without Targets During Scenarios).
- To Facilitate Comparison Of Different Trackers, Consider Generating Multiple Versions Of Each Scenario But With Reduced Levels Of Mean Signal Strength (RCS). Summary Statistics Of Metrics Could Then Be Plotted As A Function Of Mean Signal Strength. Alternatively, Repeat Scenarios With Increased Amounts Of False Signals Or Clutter

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Monte Carlo Simulation Versus Real Data

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- With Monte Carlo Simulations, Need Truth Centric Evaluation:
 - Track Numbers Are Typically Arbitrary So Not Consistent From One Monte Carlo Run to the Another Monte Carlo Run.
 - For a Given Time, It Is Preferable to Have the Same Number of Targets, Target Types, and Target Behavior for Each Monte Carlo Run.
 - For a Given Time, a Performance Metric Can Be Computed Over the Monte Carlo Runs for All the Tracks Assigned to a Specific True Target.
- With Real Data, Need Very Good Estimate of Target Truth
 - A Number of Performance Evaluations Have Been Attempted Without Good Target Truth and the Results Were Inconclusive.
 - Real Data Uncovers Unexpected Phenomena but Does Not Provide the Statistical Confidence Provided by Simulations
- Both Have Their Advantages and Testing Should Be With Both Monte Carlo Simulations and Real Data

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A Dilemma: How To Compute MOP's Over The Ensemble Of Monte Carlo Runs

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- The Problem Is That For A Scenario And A Specific Time Of Interest, The Track For A Target May **Not Be Valid** For All Monte Carlo Runs. (If Evaluate Only Valid Tracks Then Each Metric Does NOT Stand Alone But Must Be Considered in Combination with Other Metrics Such As Missing Tracks)
- Some Alternatives If The Track For A Target Is Not Valid For Some Runs. For Example, To Compute Sum Of Squares Of The Estimation Errors Over The Monte Carlo Runs:
 - ◆ Average Over Only Valid Tracks (But No Penalty For Invalid Track)
 - ◆ Insert An Upper Limit For The Invalid Tracks And Then Average Over All Tracks (Moderate Penalty For Invalid Track)
 - ◆ Compute The "Extrapolated Median"
 - ◆ Use The Best N Tracks Where N is a Specified % Of the Targets, Such As 95% (But Number Of Valid Tracks May Be Less Than N)
- **Extrapolated Median:** Sort The Valid Tracks Based On A Metric Such As Their Sum Square Estimation Errors From Smallest To Largest. Sort Only The Better Half Over All The Monte Carlo Runs And Use The Value Of The Middle One (N-th One Out Of 2N-1 Runs)

Sp207nHfVEJ.ppt Page 25

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Sp207nHfVEJ.ppt Page 26

Target-to-Track Assignment in Performance Evaluation of Multiple Target Tracking

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Abstract

Because there may be misassociations, performance evaluation of target tracking is complex due to ambiguities that can cause confusion about which target a track is following. This paper and companion PowerPoint slides presents a methodology to deal with these ambiguities so that performance metrics can be used to evaluate performance. The emphasis of this paper is on the first step of a two-step methodology, namely, the decision on which target to compare to a track so that measures of performance can be computed. However, no single methodology may be best for all the various types of tracking systems. In addition, no one methodology may be best for all the performance metrics that are appropriate to a specific system. Therefore, alternative target-to-track methods are described to permit selection of the appropriate methodologies for a specific tracking system.

Keywords: tracking performance evaluation, measures of performance, performance evaluation metrics, false tracks, error types, target tracking, multiple sensor tracking, multiple target tracking, sensor fusion, Bayesian method, Kalman filter, and target-to-track assignments.

1. Presentation Summary

Target tracking and classification problems can be broadly categorized into four generic types [1][®], as follows:

1. Sensor tracking of a single (bright) target
2. Tracking of large targets
3. Tracking of medium sized targets
4. Tracking of small targets.

Note that the size indicated in this list is in terms of the number of resolution elements or pixels of a target. Typically, a small target is less than 100 pixels. The algorithms used in the signal, image, and track processing for each of these types of problems differ substantially. Since each type of tracking problem poses different algorithm development issues, this paper and the accompanying Power Point presentation concentrate on only one type, namely, the performance evaluation of tracking of small targets using either single or multiple target tracking methods. Multiple target tracking is a relatively new field. The first book dedicated exclusively to multiple target tracking was published in 1986 [2] and a number of recent books are available, such as [3, 4].

Target tracking exhibits properties and unexpected results that are not common to most statistical estimation tasks. For example, tracking exhibits properties significantly different from signal processing; in addition to Type 1 and Type 2 errors, tracking exhibits Type 3 errors, that is a combination of both missed and false tracks [5] {3, 19}[®]. One of the major causes of unexpected results is that tracking involves random variables from both continuous sample space and discrete sample space. Accordingly, using a high fidelity simulation is a vital step in algorithm development [1] {3}. In addition, tracking performance evaluation is both complex and somewhat controversial.

[®] Note: {braces} refer to pages of the PowerPoint presentation and [brackets] refer to references in Section 2.

Ultimately, performance of tracking algorithms is judged by the success of the system that they support. Tracking performance evaluation metrics serve as a vital intermediate measure of tracking effectiveness, to diagnose the algorithms, and to predict tracking performance for use in system studies and establishing requirements. However, ambiguities can occur in evaluating performance because of misassociations [6]. Misassociations can cause missed targets and false tracks such as redundant, spurious, switched, and lost tracks [4] [5].

As a result of misassociations, it may not be clear which target a track is following, if any. Measures of performance cannot be meaningfully evaluated with the aid of a high-fidelity simulation plus field-tests (or hardware-in-the-loop testing) without first designating that target each track is following. A number of evaluation methodologies have been proposed to address this problem [17, 18] and some involve multiple frame assignment approaches [17] [5]. Care is needed not to use a methodology that gives unfair advantage to one tracking approach over another. Both the target-to-track assignment and the evaluation metrics need to be customized to the sensor application of interest and the purpose of the performance evolution task [22, 23, 24].

One relatively simple methodology for resolving these ambiguities is to use a 2-D assignment algorithm to uniquely assign the targets to tracks [6, 7] [10, 11]. The use of the statistical (Mahalanobis) distances between targets and tracks for the cost elements in the assignment matrix tends to treat the alternative tracking algorithms fairly. Then the tracking errors and other measures of performance can be computed given these unique track-target assignments. This is a two-step methodology [6, 14] [1].

In Step 1, the targets-track pairs are identified from the best unique assignment of targets to tracks. The assignment of targets to tracks could be based on the distance between each possible track-target pair and then minimize the sum of distances. If the tracker computed estimated state error covariance matrices are realistic, then the Mahalanobis distance is a meaningful statistical distance that tends to treat all applicable types of trackers fairly. An alternative is to compute the benefit of alternative track-measurement pairs based on the target source of each measurement of a track, which will be referred to simply as *track purity* [15].

The use of track purity in target-to-track assignment requires two special computations [12, 15]. First, it is necessary to determine how much each target contributed to the detection of each measurement. This computation is not practical in some high fidelity simulations that realistically simulate unresolved closely spaced objects. The second computation is to report how much each measurement contributes to each track. If a third party is evaluating performance, the tracker developer might not want to reveal this information. Knowing the target source of each measurement and how much each measurement contributed to each track permits computing a metric of the track purity of each track-target pair that can be used as a benefit value to maximize the sum of benefits with an assignment algorithm.

In Step 2, the performance evaluation metrics are computed and the results are recorded and plotted [14]. Some of the common measures of performance include the root mean sum square of the error biases, the position root mean sum square errors (rmse) and the velocity rmse; covariance consistency; the number of misassociations; track purity and duration; time to initiate tracks; and the number of missed, switched, and false tracks [8]. If the system involves multiple platforms, then performance metrics may also be needed to determine if all platforms exhibit the same information about the threat and friendly forces (SIAP). Typically for a tracking application, no single critical performance metric can be selected that can be used to evaluate the trackers. One reason a collection of metrics is needed is that usually the tracker parameters could be adjusted to favor one metric at the expense of others.

Both tracking performance and required hardware capacity should be evaluated since this is the major tradeoff in tracking. The choices of the algorithm architecture, algorithms, locations for each function, and the algorithm parameters will affect both performance and required processor capacity (plus communications load, if applicable). An example of this tradeoff between performance and required hardware resources is shown in [19][1]. This figure summarizes results of the simulation of tracking a single target with data (that included false signals) from a single passive sensor. The results are shown after seven frames of data have been processed. The tracking algorithm was similar to a single-target version of so-called multiple-target, multiple-frame assignment. The number of frames in the sliding window was varied from 1 to 6 so that the curve in the figure was obtained. The values for the horizontal

and vertical axes have been normalized by dividing by the corresponding value that is exhibited by tracking without false signals. Note that the results for the independent nearest neighbor (INN) tracking algorithm are at the left end of each of the two curves. This figure illustrates the major tradeoff between performance and the required processor capacity (processing time or required memory) for tracking with a single sensor.

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Modeling and Simulation: Key to Effective Performance Assessment of Multiple Target Tracking Algorithms

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Outline

- Introduction
- General Remarks About M&S
- M&S Architecture
- Examples
 - Measurements
 - Sensor Resolution
- Concluding Remarks

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March 2008 - Slide 2 of 32

Introduction

- Monte Carlo simulations required for comparative performance assessment/prediction for MTT algorithms.
 - Non-Gaussian measurements
 - Target maneuvers
 - Measurement-to-track association errors
 - Finite sensor resolution
- Effective M&S is critical for successful development and deployment of MTT algorithms.
- In practice, problems that can be solved are included in the M&S while others are ignored.

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Introduction

Tracking In Legacy Simulations

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March 2008 - Slide 4 of 32

Introduction

Tracking In Legacy Simulations

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March 2008 - Slide 5 of 32

Statements About Modeling and Simulation (M&S)

"All models are wrong; Some models are useful."
Henry Register, circa 1984

"Never trust a computer simulation without a back-of-the-envelope calculation to back it up."
and vice-versa

Fred Daum, 2007

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March 2008 - Slide 6 of 32

Radar Tracking of Long Range Targets

Polar-to-Cartesian Conversion of Measurements

$\sigma_r = 0.1$ m, Range = 1000 km, $\sigma_b = 1$ mrad, Bearing = 0 degree $\frac{r_b \sigma_b^2}{\sigma_r} = 10.0$

Refraction, Range, and Elevation

- Refraction increases the target's "apparent" range.
- Refraction increases the target's "apparent" elevation angle.
- Refraction changes the incident aspect angle
- Not necessarily a problem for a stand-alone sensor

Refraction and Networked Sensors

- A potential exists for network correlation error unless positions are corrected for refraction and/or the covariances are inflated.
- Adding residual refraction error does not produce the same result as refracting and then correcting.

Monopulse Processing

- Monopulse radars in BMDS typically contain 4 squinted beams

- The target echo is received with multiple beams
- Sum and difference voltage channels (in both azimuth and elevation) are established

Monopulse Response Function

Voltage Patterns for Amplitude Comparison Monopulse (ACM) System

Monopulse Measurements

For resolved measurement, variance of the angle measurement in units of beamwidth is given by

where:

$$\sigma_A^2 = \frac{1}{K_n^2} \frac{1}{2\Re_n} \left[1 + \frac{\Re}{\Re + 1} \eta^2 \right]$$

$\Re$ = SNR of the object

$\Re_n = \frac{S_o^2 + S_o^2}{2\sigma_s^2}$ = single-pulse observed SNR

$\eta = \frac{G_s(\theta)}{G_s(0)}$ = off-boresight of the sum and difference channel antenna gains

θ = off-boresight angle of the target

K_n = Monopulse error slope

Segmentation and Centroiding of Detections Wideband Radar Measurements

- dBsm threshold exceedances result from strong returns from target features
- Range sidelobe reduction blurs the point target response across multiple range cells (resolution degradation)
- Delicate balance between masking target detail with sidelobes vs blurring target detail with sidelobe reduction processing

Concluding Remarks

- In practice, problems that can be solved are included in the M&S while others are ignored.
- M&S should be pursued so that the MTT algorithms will be successful when deployed.
- Effective M&S is critical for comparative assessments of the performances of multiple algorithms

Modeling and simulation: key to effective performance assessment of multiple target tracking algorithms

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ABSTRACT

Since the errors sources associated with tracking maneuvering targets and measurement-to-track association for multiple targets are extremely complex, analytical calculation of performance are impossible for most all practical problems. Thus, one must resort to Monte Carlo simulations to assess the performance of the multiple target tracking algorithms. Therefore, effective modeling and simulation is critical to successful development and deployment of multiple target tracking algorithms. However, in many cases, the modeling and simulation is performed by the algorithm developer and it is effectively an “inverse” of the solution. Furthermore, many legacy simulations neglect the effects of sensor resolution and measurement-to-track association. Modeling and simulation for tracking algorithms should be decomposed into the “real-world,” test article algorithms, and performance metrics. In this talk, the roles of each of these items will be discussed along with critical components of effective modeling and simulation and the challenges to be faced by the developer.

Keywords: ECM, multiplatform multiple target tracking, modeling and simulation

1. INTRODUCTION

Since the errors sources associated with tracking maneuvering targets and measurement-to-track association for multiple targets are extremely complex, analytical calculation of performance are impossible for most all practical problems. Thus, one must resort to Monte Carlo simulations to assess the performance of the multiple target tracking algorithms. Therefore, effective modeling and simulation are critical to successful development and deployment of multiple target tracking algorithms. However, many legacy simulations neglect the effects of sensor resolution and measurement-to-track association. In many cases, the modeling and simulation is performed by the algorithm developer and it is effectively an “inverse” of the solution. Effective modeling and simulation requires an understanding of the problem and the impact of the environment and hardware on the tracking algorithms. Algorithm developers or engineers must view the modeling and simulation as part of the challenge to make the algorithms work effective when deployed in the field. Along these lines, modeling and simulation for tracking algorithms can be decomposed in the “real-world,” test article algorithms, and performance metrics. The roles of each of these items will be discussed along with critical components of effective modeling and simulation.

As illustrated in Figure 1, multiple target tracking can be viewed as four functional areas: detect, resolve, associate, and filter. As represented by the upper left corner, detection is the first step in the tracking of a target. Detection of the true target echoes occurs in the presence of false alarms and clutter detections. A threshold is applied to the signal amplitude to reduce the false alarm rate. However, a higher detection threshold reduces the probability of detection of the target. Thus, the detection threshold sets the false alarm rate and probability of detection and sets the performance limits of the tracker. Clutter is often countered with Doppler processing for clutter rejection and/or clutter tracking. As represented by the upper right corner, the second step of multiple target tracking is resolving the signals of closely-spaced targets into separate/isolated measurements. In radar systems, closely-spaced targets are typically resolved either in range, angle, and/or range rate. As represented by the lower right corner, the third step of multiple target tracking is assigning of measurements to tracks. This involves assigning measurements to existing tracks, initiating new tracks, and deleting tracks that are perceived not represent a truth object. As represented by the lower left corner, the fourth step involves the track filtering for estimating the position, velocity, and possibly acceleration of each target. Often, the performance of the track filter is analyzed under ideal conditions and its performance does not meet expectations when tested on actual sensor data. In most legacy simulations for tracking, finite resolution and the measurement-to-track data association are omitted from the modeling.

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Figure 1. Functional Areas Associated with Target Tracking

2. MODELING AND SIMULATION ARCHITECTURE

The architecture of the modeling and simulation program is very important. Figure 2 is given to illustrate some of the critical issues. One of the most important features of a successful modeling and simulation program is a distinction between the “real-world” models and the signal processing and tracking algorithms. The models in the real-world should be separate and different from those included in the algorithms section. One should always remember that according to Henry Register “All models are wrong [1]” and be careful not to replicate the real-world models in the algorithms. A distinction must also be made between the actual parameters in the real-world model and the perceived parameters in the tracking algorithms. Information and the associated parameters that are not known to the tracking algorithms should be represented in the real-world and access to that information must be controlled by a restricted interface and any real-world information must be reconstructed or estimated from the data that is available through the restricted interface. The interface between the signal processing and the tracking should be restricted to that anticipated in the actual sensor system. The communications from the sensor trackers to the network-level trackers should also be restricted to reflect that anticipated in the actual network. A performance assessment should also be distinctive and separate from the real-world and the algorithms, and the interface to the between the real-world and the algorithms must be controlled. A common mistake that is made in this area is the scoring of trackers immediately after a measurement update of the track filters. Scoring trackers immediately after a measurement update gives one a false expectation of performance. The scoring times and other scoring parameters should be based on the system performance metrics and set separately from the tracking algorithms as in [2].

Figure 2. Modeling and Simulation Architecture for Multiplatform Multiple Target Tracking

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Performance Assessment of Multitarget Tracking Algorithms in the Real World

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PANEL DISCUSSION :
Issues and Challenges in Track Performance Evaluation
(Organized by Ivan Kadar)

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Layered Sensing

Management Modes (Level 5)

Adapted from Billings 1997
Blasch SPIE 2003

• **Management (of sensors) - Determines the characteristics of operation**

Mgt Mode	Automation Functions	User Functions	Level of Automation	Level of Interaction
Autonomous Operation*	Complete autonomous operation System may or may not be capable of being expanded	Controller has no active role Measures fault detection Controller not usually informed	Very High	Very Low
Management by Disposition*	Essentially autonomous operation System informs controller of action responses	Controller is informed of system May intervene by reverting to lower level	High	Low
Management by Control*	Decisions are made by automation System informs controller of decisions before implementation	Controller corrects to decisions Controller is informed of decisions and decision outputs	Medium	Some
Management by Disagreement*	Automation takes action only in Level of autonomy is acceptable	Controller specifies strategy and may specify level of computer authority	Some	Medium
Interaction	Automation cues operator to key attributes and fusion incoming data	Diagnose, correlate, plan, and coordinate (fusion for action) Proactive and predictive control	High	High
Assisted Control*	Control and monitor level available Database information is available	Proactive and predictive control Voice control and coordination	Low	High
Unassisted Control*	Complete computer failure; no assistance is available	Procedural control; Unaided decision-making	Very Low	Very High

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Issues – Track Evaluation - 2008

- **Addressing the user in system management / control**
 - Track Evaluation is based on user individual needs (i.e. target location)
 - Does the Evaluation System afford the user SA for CONTROL?
- **Determining a standard set of metrics for optimization,**
 - Fusion Designers need Information Quality metrics for Standardization
 - Evaluation is hard to define and creates interface problems if not standardized
 - Does the Evaluation System afford the user TRACK INTEROPERABILITY?
- **Evaluating fusion systems to deliver timely info needs,**
 - Rigorous testing in experimental designs to define track Products
 - Does the Evaluation System afford the user TRACK in a TIMELY manner?
- **Dynamic updating for planning mission time-horizons,**
 - Track evaluation from a data approach does not help prediction assessment
 - Mission Management evaluation includes time-based exploratory reasoning
 - Does the Evaluation System afford the user GAMING Solutions?
- **Designing interfaces to support track eval/assessments**
 - Would allow a team of people to interface distributively → net-centric
 - Does the Evaluation System afford the user Info Needs for REASONING?

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Fusion Process

Background

- E. Blasch, I. Kadar, J. Salem, M. Kokar, S. Das, G. Powell, D. Corhill, and E. Ruspini, "Issues and Challenges of Knowledge Representation and Reasoning Methods in Situation Assessment (Level 2) fusion", *Journal for Advances in Information Fusion*, 2006.
- D. L. Hall and J. Llinas, "Introduction to Multisensor Data Fusion", *Proc. of IEEE*, Vol. 85, No. 1, pp. 6 – 23, Jan 1997.

Challenges and Limitations (Level 4)

- Incorporation of **mission objectives/constraints**
- Environmental **context** for sensor utilization
- Conflicting objectives (e.g. detection vs. accuracy)
- Dynamic algorithm selection/modification
- Diverse sensors

Current Status

- Robust system for single-sensor sys.
- Operations research formulation
- Limited approximate reasoning
- Focus on **MOP** and **MOE****

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Performance Measures
Fusion Quality of Service Metrics
Blasch 2003

COMM	Human Factors	COMPASE	ATR	TRACK
Delay	Reaction Time	Timeliness	Acquisition /Run Time	Update Rate
Probability of Error	Confidence	Confidence	Prob. (Hit)	Probability of Detection
Delay Variation	Attention	Accuracy	Prob. (FA)	Covariance
Throughput	Workload	Throughput	Positional Accuracy	No. Targets
Cost	Cost	Cost	# Images	No. Assets
Stallings 2002	Wickens, 1992	Blasch, 2003	Collection platforms	COMPASE Morrison
				Blasch, (DDb) Hoffman 2000

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MOP / MOE
Blasch SPIE 2003

User

MOO – Measures of Objectiveness

- Review for reasonableness and acceptance
- Degree of protection of own forces, degree of campaign shortening, attrition of foe capability to wage war

MOE – Measures of Effectiveness

- Military worth or targets nominated for attack, required sortie rate, attrition, platform numbers required, platform /sensor costs

MOP – Measures of Performance

- Coverage geometry and continuity, # of targets detected, ID status, C2 timeliness, etc.

Model Scenario & Input

- Sensor wavelength, resolution, mode, range; platform and target location/trajectory; environment, Wx, command and control characteristics, fusion, detection, and ID methods and various assumptions, e.g. tactics

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Fusion ID Trade-Space

- FITE Equation**

$$p(B|R) = \sum_{\text{range}(A)} p(B|A, I) p(A|I', R) p(I|R)$$

$$P_{ID} = \sum_{\text{range}(B)} p(B_A = r_i | R_i = r_r, R_c) p(R)$$
- Elements**
 - Main variables
 - Real and Visible worlds, ATR outputs, Bayes Fusion outputs
 - Key dimensions of variables ("Subscripts")
 - Type: OGS, Uncertainty
 - Fuser's models ("Primed models")
- Considerations**
 - Monte Carlo solution
 - Hyper-distribution avoidance ("Dashed lines")
 - Source-to-source dependencies ("Link models")
 - Large number of models
 - Operating Conditions' (OCs) fundamental role

Real World

Bayes Fusion

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Track Performance Issues - 2008

- Issues**
 - Level Track Quality by **quantity** (*throughput*) – for statistical tests
 - Timeliness** of control sensing needs (e.g. parameters to sense)
 - Use of **domain knowledge** to predict future needs (i.e. **context**)
 - Multiple users have differing levels of process needs in a **distributed fashion** from the same situation.
 - Varying **fidelity of confidence** reporting of impending threats and situations
- Challenges**
 - Pedigree analysis** to backtrack through associations
 - Time Horizons of control** actions from/ to user (i.e. priority schemes)
 - Performance models** of track analysis to afford level 4 sensor management
 - Evaluation Presentation** that explains many metrics simultaneously.
 - Unified **Set of metrics** that afford level 2/3 processing that can be optimized in a level 4 objective function

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Track and ID Display

Blasch, 1998, IEEE AES Mag

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Performance Assessment of Multitarget Tracking Algorithms in the Real World

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ABSTRACT

There are hosts of target tracking algorithm approaches, each valued with respect to the scenario operating conditions (e.g. sensors, targets, and environments). Due to the application complexity, no algorithm is general enough to be widely applicable, nor is a scenario narrow enough for a tailored algorithm. Thus, to meet real world goals, multitarget tracking (MTT) algorithms need to undergo performance assessment for (1) bounding performance over various operating conditions, (2) managing expectations and applicability for user acceptance, and (3) understanding the constraints and supporting information for reliable and robust performance. To meet these challenges, performance assessment should strive for three goals: (1) challenge problem scenarios with a rich variety of operating conditions, (2) a standard, but robust, set of metrics for evaluation, and (3) design of experiments for sensitivity analysis over parameter variation of models, uncertainties, and measurements.

Keywords: Tracking, Information Fusion, Performance Evaluation, Metrics, Scenarios

1. INTRODUCTION

Recent events have changed domain applications for multisensor information fusion and target tracking from locating a small number of large targets to maintaining tracks on a large number of targets of varying sizes. Increasingly complex, dynamically changing scenarios have evolved that require intelligent tracking strategies. These intelligent strategies have to be evaluated over various locations, observing changing targets, and detecting unknown threats. Such a scenario of interest for “*Layered Sensing*” is an urban setting for Homeland Defense. Layered sensing incorporates many research issues in intelligent tracking, sensor development, and information fusion. Figure 1 shows a layered sensing scenario that incorporates high-altitude platforms for target detection, surveillance unmanned aerial vehicles (UAVs) for target tracking, and individual audio reports from ground stations for target identification. To assist in the coordination of these layered assets, it is imperative to (1) understand the performance driving each system, (2) determine the metrics for effective collaboration, and (3) proactively utilize the systems relative to the real-world scenario of interest.

Figure 1. Layered Sensing.

Performance assessment of multitarget tracking (MTT) for the real world requires (1) pragmatic understanding of the algorithm designs, portability and applicability, (2) detailed testing over various scenarios and operating conditions, and (3) focused assessment of sensitivity analysis and performance metrics [1] through tailored design of experiments. While the

MTT community has made progress in algorithm comparisons and metrics through the work of Blair in the Benchmark problems [2, 3], metrics and tailored target tracking performance evaluations from Drummond [4, 5, 6, 7, 8], and algorithms from Blackman [9] (as well as many others in the community e.g. [10, 11, 12]); there still is a need for reliable and designed testing scenarios to increase the understanding of the MTT approaches for the operational use of the techniques.

Real world applications of target tracking are embedded in larger operational goals such as surveillance, targeting, and force assessment that includes both *entity estimation* and *situation control*. The Information Fusion Community has adopted the Data Fusion Information Group (DFIG) model, shown in Figure 2, with emphasis placed on sensors and their estimations from the real world. Target tracking is but a piece of a larger information fusion system including user requirements, registration algorithms, and sensor management. Level 1 fusion, which includes target tracking and identification, is merely a technique to provide situational awareness. Situational awareness in and of itself is a picture of the environment that requires situation assessment (i.e. number of targets, movement of targets, and the identity of targets). This information aggregation supports a user's real world decision-making goals of security, strike packages, and positioning forces. However, the tracking performance assessment of the situation can also be viewed as a control problem. The control problem requires tools and techniques for decision support such as metrics and analysis to place sensors, waveform diversity to choose operating modes, and situation characterization to relay information to other distributed users. The real world is complex; however, effective methods of tracking performance analysis will aid users to appreciate and trust tracking systems, utilize the tracking results for situational awareness, and adaptively control sensors for effective performance.

Figure 2. DFIG 2004 Model (Replacing the JDL Fusion Model) [13]

This paper supports a plenary discussion on ideas to enhance research in MTT for real world instantiation of MTT algorithms. It is not meant to serve as a critic of the current state of the art, but rather to suggest ideas for future improvements and directions for the community to be able to (1) transition the techniques, (2) manage expectations for groups incorporating MTT into larger designs, and (3) develop the resources available for the next generation of tracking researchers.

Three areas of support that are important to the community are (1) scenarios [14], (2) metrics [15, 16, 17], and (3) design of experiments [18]. While these ideas are not novel, the packaged details in a “Challenge Problem” would support the community. As indicated, Dale Blair has supported a Benchmark challenge problem for many years [2], Oliver Drummond has supported a various host of metrics [19], and Jim Llinas and *Center for Multisource Information Fusion* [20] have done initial work on MTT design of experiments. Building on these developments, the MTT community can support future challenge problems so that continued understanding, testing, and focused assessment can improve MTT research developments.

The paper describes brief attributes where MTT performance assessment can be furthered for real world realization of the techniques. Section 2 starts with scenario designs in Challenge Problem development. Section 3 places emphasis on a robust set of metrics that needs to be adopted as a standard for the tracking community. Section 4 describes a design of experiments approach which typical complex systems designs utilize for understanding. Section 5 draws conclusions.

2. SCENARIOS

Tracking algorithms for the real world require a pragmatic understanding of the complexities surrounding the application such as the number and types of targets, the sensors including their physical parameters and communication links, and the varying environmental conditions.[21] Utilizing static and dynamic environmental conditions can lead to host of challenges for MTT algorithms. Typically, with weak applicability to the real world, MTT algorithms focus on performance assessment over different target densities, ordered set of detection policies (e.g. Probability of Detection > 0.8), and various forms of clutter (e.g. Gaussian and Poisson).

As example of challenging scenario designs, the DARPA Dynamical Tactical Targeting (DTT) program [22] tested a variety of scenarios and evaluated system performance. Figure 3 represents the design space of different scenarios available for a given MIDB (Mission Data Base), Nominated Area of Interest (NAI), and air task order (ATO) of mission objectives. After the selected scenario conditions for each run were determined, a simulator was used to instantiate the truth information, such as actual target behaviors and sensors measurements. The simulator used the mean values and variance bounds associated with selected factors to create a half-day scenario which afforded a longitudinal performance analysis based on ergodic assumptions.

Figure 3: Scenario Parameters. [22]

While the various MTT Performance Assessment techniques have been documented in the literature [23, 24], there is a long way ahead for reliable and robust performance assessment of real world systems. Issues of communications, measurement uncertainties, and models are important. As shown in Figure 4, there are many functions surrounding target tracking and identification. The first issue is to characterize the sensitivity of MTT systems to *ancillary support data*. With today's resources of GPS, terrain maps, and weather updates; it is important to utilize and capitalize on these products to support MTT assessment. It would be naïve to think that future MTT designs would not utilize this information. Likewise, the reliance on these technologies also becomes a sensitivity parameter of performance. For instance, research in terrain-aided navigation (akin to dead reckoning) is of interest to support navigational systems with a GPS dropout. Thus, MTT should explore scenarios over which reliable and unreliable support data is available. Additional ancillary information for real world testing includes data truthing, metric evaluation, and careful sensitivity analysis over operating conditions for model enhancements.

Figure 4: Support Needs for Target Tracking Performance

The second aspect of scenario designs includes **modeling**. Modeling incorporates target kinematic and behavior models, sensor exploitation performance models, as well as the environment performance models (e.g. Digital Terrain and Evaluation (DTED) models). The tight restriction of MTT evaluation has typically included simple kinematic models for target behaviors. One way to account for the simplistic models is to use a Variable-Structure Interacting Multiple Model (VS-IMM) or Multiple Model Adaptive Estimation (MMAE) approach to fuse the models to cover varying target behaviors. Another issue of importance in the performance analysis is the track accuracy based on the smoothing of models or the track loss for the tailored use of a single model. Finally, the use of models is critical to sensor management which determines which sensors are positioned for measurements. If the sensor models are simple detection approaches, it does not afford a rich analysis of feature assessment for track maintenance. In summary, MTT performance assessment needs to refine the sensitivity of the results by way of determining the effects of models on MTT performance.

The third aspect of scenario design is related to MTT **distributed information**. These distributed aspects include the communications and user involvement. Information theory details the performance bounds relative to bandwidth and capacity. If future MTT systems are to be deployed for real world applications, there is a need to understand the track life and track maintenance of systems when there are sensor delays, data drop out, bit errors, and performance degradation factors. Similarly, real world tracking is not only based on surveillance, but user needs. The goal for MTT performance assessment is in “Performance Driven Sensing” when a true understanding of operator placement of the sensors for measurement becomes an integral part of the MTT algorithm. Rarely, is a high-value sensing asset allowed to operate autonomously. Furthermore, the more reliable and diverse systems are under management contention between commanders. Thus, a performance assessment should include distributed analysis of communication constraints and user control issues.

To utilize the various parameters in the real world analysis, the MTT community should support challenge problems and performance models to enhance the understanding of real world issues in MTT assessment.

2.1. Performance Models

A sensor model is derived from physical, simulated, or empirical analysis. The physical parameters can be incorporated into physical or analytical models such as the radar equation. A more detailed analysis of the sensor system feeding an MTT system would be an **exploitation model**, such as a SAR performance model [25]. There are a host of other sensors for MTT such as HSI or EO sensors [26, 27] that need development for models that are verified and validated. Second, there is a need for target models. In the case of MTT, many stationary target models exist such as the CAD models detailed in the DARPA MSTAR program.[28] Third, environment models such as DTED, Google Maps, and other data are available. Weather and terrain contour maps could aid in the understanding of target movement. The documentation and model fidelity [29] (for a given scenario) can be included in a benchmark challenge problem for MTT comparison and evaluation.

2.2. Benchmark Challenge Problems

Blair [2] created a benchmark challenge problem. The ATR Community has produced a set of challenge problems detailed by Arnold [30]. A scenario includes various kinematic target movements, possible sensor signals and target signatures, and terrain details. Ross *et al.* [31] and the MSTAR team created a set of operating conditions over sensor, targets, and environments.

As a quick summary, the following pieces constitute a “Challenge Problem:” [30]

- Problem Definition: The scope and significance
- Data: Applicable data for the defined problem
 - Tools for reading and processing data
 - Suggestions on training and test sets
 - Characterization of the data
- Goals: Research challenge questions and suggested experiments
- Metrics: Guidance on reporting results
- Tools: Baseline code & results: Shows reproducible minimum performance for the defined problem

Scenarios provide data and support documentation for real world analysis either through analytical, simulated, or empirical results; however from software design “You can’t control what you can’t measure” [32].

3. MTT PERFORMANCE METRICS

What you measure is what you get. To support performance assessment, there is a need for an authoritative standard, defined calculations, and suggested sensitivity metrics from which to test and evaluate algorithms. For example, military MTT is based on a host of metrics that start with the measurement (detection and cueing) and end with (engagement and assessment) as shown in Figure 5. MTT metrics can be viewed as a *producer of* or *consumer of* the information. If the user is only interested in target identity, then MTT kinematic behavior assessment would provide additional information for a goal outside traditional MTT processes. Likewise, MTT consumes the uncertainty and detection metrics from the sensors. Together the MTT system uses and consumes the metric information for analysis in conjunction with a sensor, algorithm, and platform manager.

Figure 5: Kill Chain [33]

A host of MTT metrics have been described by Drummond, Blair, and Li. In each case, the metrics are associated with the algorithms themselves and provide a good taxonomy of issues to consider. In future real-world applications, there is a need to relate the metrics to user concerns above and beyond the standard metric of RMS position error for target location. One example is the communications community with a standard set of *Quality of Service* (QoS) metrics.[34] From the list of metrics, and important metric not currently considered for future real-world MTT analysis, includes *Timeliness Variation*. Sensor and information fusion systems require that the sensed information be communicated to the tracker in a timely manner with the associated throughput restrictions for hardware limitations. Communication methods transfer data from the sensor to the MTT center through routers, which can be modeled as a queue. For example, wireless systems will require ad hoc configurations of routers to transfer the information *directly* from the sensors to a mesh network. The mesh network, consisting of these routers, would then enable rapid transfer of the information to a distributed set of MTT sensors. Thus, to afford proactive MTT strategies, we need to consider the communication delays for timely decision making. For future MTT systems the *Quality of Information* will be important [35] as a sensitivity parameter as well as achieving the high fusion data quality (FDQ) [36] which may not be always commensurate with high QoS.

3.1. Standardizing the MTT Metrics to Include System Metrics

To design a complete MTT system, we need to address *user information needs* in the design and development process. Blasch [37, 38] explored the concepts of situation assessment (SA) by detailing the user needs of **attention**, **workload**, and **trust** which can be mapped into metrics of **timeliness**, **throughput**, **confidence**, **utilization**, and **accuracy**. Workload and attention can be reduced if the MTT system cues the operator to a few selected target descriptions (hence workload and timeliness). If the MTT performs better against a known *a priori* data set, accuracy and confidence increase, enhancing operator trust.

Dynamic situation analysis has three components: (1) dynamical responsiveness to changing conditions, (2) situational awareness, and (3) continual analysis to meet throughput and latency performance requirements. The combination of these three entities is instantiated by a tracking and ID [11, 12] system, an interactive display to allow the user to make decisions,

and metrics for replanning and sensor management [39]. To afford interactions between future MTT system designs and users information needs, metrics are required. The MTT metrics should include timeliness, accuracy, throughput, confidence, and cost. These metrics are similar to the standard quality of service (QoS) metrics in communication networking [36, 40] and theory and human factors literature, as shown in Table 1 [1].

Table 1: Metrics for Various Disciplines [1]

COMM	Human Factors	Info Fusion	ATR/ID	TRACK
Delay	Reaction Time	Timeliness	Acquisition /Run Time	Update Rate
Probability of Error	Confidence	Confidence	Prob. (Hit), Prob. (FA)	Prob. of Detection
Delay Variation	Attention	Accuracy	Positional Accuracy	Covariance
Throughput	Workload	Throughput	No. Images	No. Targets
Cost	Cost	Cost	Collection Platforms	No. Assets

The detailed metrics are required for a **comparison analysis**. For example, it is widely known that the interacting-multiple model (IMM) is best for maneuvering targets. In order to convey the results of tracking algorithm approaches, care must be taken to ensure that the performance analysis of the algorithm versus the data quality. For example, X Rong Li [41] has proposed relative metrics for analysis of trackers to separate the tracker performance from the quality of the measurements. Note: An *IEEE Aerospace and Electronics Systems* (AES) Standard Committee led by Blair is working on track fusion and target tracking terminologies.

3.2. System Performance Metrics

The goal of any multisensor system intelligent MTT analysis is to have a track gain over improved lifetime, timeliness, accuracy, and throughput. The information fusion gain can be assessed as Measures of Effectiveness (MOE) or Measures of Performance (MOP). MOPs include the standard MTT parameters of number of targets tracked, throughput, time, and P_D . MOEs include force protection, situation analysis, and event occurrence.

MTT performance metrics includes number of targets tracked; however, the system performance metric is throughput. **Throughput** can be determined as the average rate, peak rate, and variability of the system to deliver information to the user. The **average rate** (events processed / time) is the average load that can be sustained by the sensor over an extended period of time. The **peak rate** tells the network what type of surge traffic must be coped with, either by dedicating data-rate capacity or by allocating sufficient buffer space to smooth out measurement surges. **Variability** measures the source burstiness and is an indication of the extent to which statistical multiplexing is needed for distributed tracking.

Timeliness is QoS metric for system performance; however, system **Delay** (or *latency*) is a system-level metric which can be measured with time to assessment or delay variation. *Transfer delay* measures the delay imposed by the network on data transferring from a source to a destination. *Delay variation* is an important parameter for real-time applications, in which the data displayed at the destination must appear at a smooth continuous rate matching the rate generated at the source. Some of these issues were discussed in [36, 40] as they effect distributed tracking and fusion systems performance

3.3. Robustness

The MTT community is familiar with root-mean square error (RMSE), track purity, and track life [15]. While each of these is based on the scenario, it lends itself to false understanding of the tracker itself. To look at the tracker, many times the covariance information is used as a measure of the relative performance of the track estimation [9]. The MTT community, already accustomed to a system metric of track accuracy and track lifetime, should be acknowledging a system metric of robustness. **Robustness** includes specifications of designs (e.g. robust design), trusted reliability (e.g. robust decision making and estimation e.g., [42, 43, 44, 45, 46], and insensitivity to parameter variation (e.g. robust control). The goal for the MTT community is to explore the sensitivity of performance over a variety of conditions to ensure that the tracker designs relate to robust performance [47, 48]. Essentially, a robust assessment, extending from confidence and reliability [49], would lead to performance bounds that give an envelope of performance to support a managed expectation to users of MTT performance. In summary, the choice of metrics, either detailed in the challenge problem or supported by the tracking community, needs to be standardized, consistently calculated, and allow for sensitivity studies.

4. DESIGN OF EXPERIMENTS

DOE supports the valid and verifiable direct, indirect, and interactive effects between the various operating conditions over the changes in these scenarios for a sensitivity analysis. Since real-world MTT incorporates a host of interactive effectiveness in a complex environment, there is no such analytical model to cover all aspects of the research. While the analytical approach is not without merit, only parts of the problem can be modeled. With some models, simulation studies can lead to an understanding of the domain. The MTT community is rich with papers utilizing kinematic models with simulated data to test out a set of operating conditions. There are even studies that include analysis over an empirical data set. However, the issue of the “Real World” incorporates both the expected and the unexpected events in a scenario. Thus, the MTT community needs to realize that the tracker is a piece of a larger complex system. Acknowledging that MTT is in a complex system leads one to seek complex performance analysis for which a standard approach is Design of Experiments.

Design of Experiments (DOE) [50] is a methodical way to control the performance assessment by changing certain parameters and regressing over the outcome. The purpose of using formal DOEs is to achieve the highest level of statistical significance of the tests while requiring the minimum experimentation e.g., [51]. DOE includes a host of techniques used to support the validity and reliability of testing complex systems while systematically understanding the process. Measures of Merit (or Figures of Merit) such as accuracy, confidence, and timeliness can be studied by changing parameters. One example is shown below of a DOE for MTT [22].

To effectively evaluate system performance, three types of parameters are assessed: (1) **constants** (e.g. NAI); (2) Monte Carlo **variables** (e.g. sensor variation), and (3) **factors** that change (e.g. number of targets) [21]. Table 2 shows the DOE analysis for the target, sensor, and environment EOCs (experimental operation conditions [32]). Constant parameters were determined from either un-modelable effects, issues that did not affect the outcome, or real-world operating conditions. Constant target behavior includes emissions and on-road travel while variable target behavior includes move-stop-move cycles, paths, and speed. The sensors and platforms are a result of the mission scenario. The sensor variables included exploitation accuracy and sensor factors including an On/Off bias selection. The largest category of scenario OCs is from the environment which includes weather, nominate area of interest (NAI) selected by the user, facilities of target initiation/termination, terrain/road conditions, and ‘no-fly zones’. For each scenario, the NAI was fixed and available terrain and weather data provided.

Table 2: DOE of Test Scenarios. [22]

OC Category	Parameter	Flat Terrain	Mountainous
Targets	Targets	6, 12, 25	1, 2, 5
	Moving Confusers (Dens. / AOD)	Low(10), 50 , High (1000)	Low (0), Med (10), High (25)
	Routes-Stop-Move	Variable	Variable
Sensors	Initial Start Points	Variable	Variable
	Bias	On/Off	On/Off
Environment	‘No Fly’ Zones	Variable Area Locations	Variable Area Locations

5. TRANSITION TO THE REAL WORLD

Together the scenarios, metrics, and DOE lead to focused challenge problem sets for a performance analysis and repeatable understanding. Layered sensing can mean various things depending on the operating conditions. However, there are common themes associated with layered sensing MTT, such as dense targets, roads and infrastructure, and known sensor measurements. Scenarios require many novel MTT applications that are not well researched such as evaluation metrics, proactive control of sensors, distribution of information to users, usefulness of pedigree information, and robust metrics. To determine successful intelligent MTT processing strategies, an evaluation assessment is needed to determine if developments have increased the capabilities of the MTT solutions. Figure 6 shows a process model [52] detailing the processes of innovation to design to operations. From the MTT analytical model studies, towards simulations with generated and empirical data, MTT systems are ready for real-world DOE testing.

Figure 6: MTT Performance Assessment Process model for real world transition.

6. CONCLUSIONS

This position paper evaluated an MTT performance assessment from the standpoint of years of MTT research in designs, metrics, and simulated studies with the systematic view of transitioning these systems to real world capabilities. Whether the users are single sensor operators or part of a team, as shown in Figure 7, there is a need for system-level understanding of MTT performance. The ideas presented that support the transition of MTT systems to the real world include (1) enhanced scenarios delivered to the community by way of challenge problems and sensor, target, and environment models, (2) standardized metrics and appropriate methods for calculating the metrics, and (3) systematic testing of the complex system-level analysis through design of experiments to determine the sensitivity of the MTT solutions. With these ideas, the MTT community can manage user expectations, bound performance for sensor management, and determine the research areas of need for the future robust MTT success.

Figure 7: Users of MTT Systems requiring Performance Assessment.

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Consumer Reports Approach for Assessing Multi-target Trackers

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SPIE Panel on "Issues and Challenges in Performance Assessment of Multi-target Tracking Algorithms with Applications to Real-World Problems"
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Can We Assess MTTs Like Consumer Reports (or Car Magazines) Assess Cars?

- There are many multi-target tracking algorithms (car models)
- They are developed for different tracking applications – surface, ground, air, missile (sports car, family cars, minivans, SUVs)
- Users need help in
 - Understanding how algorithms perform
 - Selecting right algorithm for their application
- We need systematic approach to assess tracking algorithms (Annual Consumer Reports Issue on car buying)

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Car Reviews versus MTT Reviews

- XXX Sedan
 - System description
 - Engine – 4 cylinder
 - Transmission – independent
 - Brake – front disc/rear drum
 - Steering – rack and pinion
 - Component performance
 - 0 to 60 mph – 10 sec.
 - 60 to 0 mph – 140 ft
 - Top speed – 100 mph
 - Cornering – 0.8 g
 - Performance on test range
 - Time to complete – 30 minutes
 - Mpg – 40
 - Performance on road or off-road
 - Time to complete – 45 minutes
 - Mpg – 25
- YYY Multi-target Tracker
 - Algorithm description
 - Tracking filter – VSIMM
 - Association – track-oriented MHT
 - Component performance
 - Filtering benchmark – xx m position accuracy
 - Association benchmark – yy% correct association
 - Performance on simulated data
 - Performance on real data

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Generic Multi-target Tracking Algorithm Architecture

```

graph LR
    Measurements --> Tracking_Filter
    subgraph Tracking_Filter [Tracking Filter]
        Prediction --> Estimation
        Estimation --> Prediction
    end
    Tracking_Filter --> Tracks
    Tracks --> Association
    Association --> Prediction

```

- Tracking filters
 - Extended Kalman filter
 - Interacting multiple models
 - Particle filters
- Association algorithms
 - Nearest neighbor
 - Global nearest neighbor
 - Multiple frame association / multiple hypothesis tracking

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Component Performance Assessment

- Tracking filters
 - Performance of target state estimation assuming no association problem (e.g., single target or widely separated targets)
 - Need benchmark tests for tracking filters
 - Target motions with different maneuverability
 - Sensors with different errors and revisit rates
- Association algorithms
 - Performance of data association (measurement to track or track to track) assuming trivial target estimation problem (e.g., static target or target with no process noise)
 - Need benchmark tests for association algorithms
 - Scenarios with different normalized target densities

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Context Metrics to Characterize Problem Complexity

- Need simple parameters to characterize problem complexity
- Possible context metric for state estimation: target maneuvering index
$$\lambda = \frac{\sigma_v T^2}{\sigma_w}$$

σ_v : Process noise standard deviation
 T : Revisit interval
 σ_w : Measurement noise standard deviation
- Possible context metric for association: normalized target density
$$\beta = D_s |R|^{1/2}$$

D_s : Density in measurement space
 R : Measurement error covariance

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System Performance – Simulated Data

- Performance of MTT is more than collecting individual performance of tracking filters and association algorithms (car performance is more than individual engine, transmission, and brake performance)
- Testing with simulated data of entire scenarios provides MTT system performance in controlled situations
- Challenges with simulated data
 - Design of scenarios to cover problem space
 - Fidelity of sensor and target models
 - Data characterization (in terms of context metrics)
 - Availability of benchmark data

System Performance – Real Data

- Simulated data is not real (we need to drive on a REAL road)
- Testing algorithm with real data will reveal effects of imperfect target and sensor models
- Challenges with real data
 - Planning for data collection (targets, sensors, location, instrumentation)
 - Limited data sets due to cost of collection
 - Determining truth
 - Assigning measurements to truth

Is It the Car or Is It the Road?

- Performance of MTT depends on algorithm itself and problem complexity
 - Easy scenario - any algorithm will work
 - Difficult scenario - no algorithm will work
- Context metrics should be displayed with performance metrics

Summary

- Multi-target tracking algorithm performance assessment can learn from Consumer Reports assessment of cars
- Need
 - Component performance assessment
 - System performance assessment with simulated data (driving on test tracks)
 - System performance assessment with real data (driving on real roads)
- Challenges include
 - Selecting performance metrics
 - Characterizing problem space for testing (context metrics)
 - Designing benchmark test data
 - Generating enough simulated data at right level of fidelity
 - Collecting representative real data with ground truth

Consumer reports approach for assessing multi-target trackers

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ABSTRACT

This paper presents an approach for assessing multi-target trackers analogous to that used by *Consumers Reports* and car magazines in assessing cars. Car assessments usually contain a description of key components such as engine and brake, component performance such as acceleration and braking times, performance on test range, and performance on the road. The analogous assessment for trackers consists of a description of state estimation and association algorithms, performance of these individual components, system performance with simulated data, and system performance with real data.

Keywords: performance assessment, tracking filters, association algorithms

1. INTRODUCTION

Many civilian and military applications such as air traffic control and battlefield surveillance requires the tracking of multiple targets using data from one or more sensors. Since many multi-target tracking algorithms have been developed over the years, the user is faced with the problem of selecting the right algorithm from many alternative algorithms. More specifically, the user needs help in understanding the performance of the algorithms and selecting the right algorithm for the application.

This algorithm assessment and selection problem is quite similar to that of buying a car. There are many types of cars, e.g., sports cars, family cars, minivans, and sport utility vehicles (SUV's), analogous to different algorithms for tracking surface, ground, air, and space targets. However, car buying is now a fairly systematic process. For example, every April *Consumer Reports* publishes the annual car buying issue that contains information on basically all the cars sold in the United States. By consulting this issue, a car buyer can compare different cars and select one that meets his or her needs and budget. The objective of this paper is to describe a systematic approach for assessing tracking algorithms analogous to that for assessing cars. This assessment approach can potentially simplify the task of matching algorithms to applications.

The rest of this paper is organized as follows. Section 2 presents a structure for assessing multi-target tracking algorithms that is motivated by that used for assessing cars. Section 3 discusses the main components in a multi-target tracker (MTT) and the assessment of individual components. Section 4 describes system performance assessment with simulated and real data and the need to characterize the complexity of the problem.

2. ASSESSMENT STRUCTURE

A car review in *Consumer Reports* or car magazines such as *Car and Driver* or *Road and Track* usually has information on the basic components such as engine, transmission, brake, steering, and performance results on the individual components such as time from 0 to 60 miles per hour, braking distance from 60 to 0 miles per hour, etc. These component performance results are augmented by test results on both test ranges and under realistic driving conditions. A similar structure can be used for assessing multi-target trackers. The assessment will start with a description of the component algorithms such as those used for tracking and data association, and the performance of these component algorithms. These will be followed by system level performance with simulated data and real data such as those collected in flight tests. Table 1 compares the car reviews with MTT reviews.

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Table 1: Car reviews and MTT assessment have similar structures

XXX Sedan	YYY Multi-target Tracker
<ul style="list-style-type: none"> System description <ul style="list-style-type: none"> Engine – 4 cylinder Transmission – independent Brake – front disc/rear drum Steering – rack and pinion Component performance <ul style="list-style-type: none"> 0 to 60 mph – 10 sec. 60 to 0 mph – 140 ft Top speed – 100 mph Cornering – 0.8 g Performance on test range <ul style="list-style-type: none"> Time to complete – 30 minutes Mpg – 40 Performance on road or off-road <ul style="list-style-type: none"> Time to complete – 45 minutes Mpg – 25 	<ul style="list-style-type: none"> Algorithm description <ul style="list-style-type: none"> Tracking filter – VSIMM Association – track-oriented MHT Component performance <ul style="list-style-type: none"> Filtering benchmark – xx m position accuracy Association benchmark – yy% correct association Performance on simulated data Performance on real data

3. COMPONENT DESCRIPTION AND PERFORMANCE ASSESSMENT

Performance assessment of multi-target trackers requires identifying the components in the algorithm and the performance of the individual components. With the exception of association free algorithms such as those described in [1], most multi-target tracking algorithms consist of the following steps (Figure 1): predicting the target states of the tracks to the reporting time, associating the reports to the tracks, and updating (estimating) the target states given the associated reports. Furthermore, prediction and estimation are usually implemented together in a tracking filter.

Figure 1: Generic MTT consists of tracking filter and association algorithms

Possible tracking filters include extended Kalman filters, interacting multiple models (IMM), and particle filters. Possible association algorithms include local nearest neighbor, global nearest neighbor, and multiple frame association or multiple hypotheses tracking.

Component performance assessment includes tracking filter performance assessment and association algorithm performance assessment. If the tracking filter in a MTT cannot be isolated for testing, its performance can be assessed by using data sets with no association problems, e.g., data from a single target or multiple widely separated targets. Benchmark tests for tracking filters should include target motions with different maneuverability and sensors with different errors and revisit rates. Similarly, association algorithms should be assessed stand alone with data sets with little difficulty in target state estimation, e.g., static target or targets whose models have no process noise. Benchmark tests for association algorithms should include scenarios with different normalized target densities.

Performance should be assessed for problems whose complexity can be parameterized easily. One way of characterizing complexity is by context metrics [2]. A possible context metric for state estimation difficulty is the target maneuvering index $\lambda = \sigma_v T^2 / \sigma_w$ where σ_v is the process noise standard deviation, T is the revisit interval, and σ_w is the measurement noise standard deviation. The equivalent context metric for association is normalized target density $\beta = D_y |R|^{1/2}$ where D_y is the density in measurement space and R is the measurement error covariance.

4. SYSTEM PERFORMANCE ASSESSMENT

The performance of a system depends on how the components work together. This is true whether we are dealing with a car or a multi-target tracker. Thus, it is important to assess the performance of the system as a whole in addition to that of each individual component. System performance should be assessed under both highly controlled conditions (test range for a car and simulated data for MTT) and realistic conditions (actual roads for a car and real data for MTT).

Testing with simulated data allows performance assessment over large parameter spaces and is frequently the only way to find the performance envelope of an algorithm. Even though simulated data is generally cheaper to generate than real data, designing scenarios to cover enough interesting cases is still non-trivial. Target and sensor models are used to simulate the data. Highly detailed models produce realistic data but require significant processing sources and long simulated times. Thus selecting the appropriate model fidelity is very important. To facilitate algorithm assessment and reduce cost, the multi-target tracking community should develop benchmark data sets (e.g., [3]) for different tracking problems just like test tracks for testing cars.

Just as a car buyer wants to test drive the car on the real road, testing MTT with real data is very important because real data can reveal the effects of imperfect target and sensor models on the algorithm. Since real data collection is expensive, only limited amount of data can be collected. Thus it is important to carefully plan the target types and trajectories and the placement of the sensors. Instruments have to be placed on the targets to record accurate locations. Performance assessment of multi-target trackers requires assigning tracks to target. For simulated data, one can trace the origins of the measurements in the tracks to the targets and use them for the assignment. Since this tracing of measurements to targets is no longer possible in real data, another way of assigning tracks to targets has to be found.

Just as a high performance car cannot go fast on a poor road, the performance of MTT depends on the algorithm itself and problem complexity. Almost any algorithm will perform well on an easy scenario but almost any algorithm will fail for a difficult problem. Thus it is important to characterize the problem complexity when assessing algorithm performance (Figure 2).

Figure 2: Both performance and context metrics should be displayed in performance assessment

5. SUMMARY

Multi-target tracking algorithm performance assessment can learn from *Consumer Reports* assessment of cars. Specifically, performance assessment should include component performance assessment, system performance assessment with simulated data (driving on test tracks), and system performance assessment with real data (driving on real roads). Challenges include selecting the appropriate performance metrics, characterizing problem space for testing (context metrics), developing benchmark test data, generating enough simulated data at right level of fidelity and collecting representative real data with ground truth

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Challenges and Recent Advances in Estimation Performance Evaluation

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Scope of Presentation

- Tracking relies on estimation, but
 - Tracking has its own issues
 - We address
 - estimation performance directly,
 - tracking and data fusion performance indirectly
- that is, issues **common** to estimation, tracking, and data fusion performance evaluation

Outline

- Background
- Limitations and drawbacks of existing metrics
- Challenge 1: Comprehensive evaluation
- Challenge 2:
Evaluation **without** knowing ground truth
- Challenge 3: Algorithm comparison and ranking
- Summary

Limitations of Existing Metrics

- Need knowledge of ground truth
- Lack of comprehensive metrics:
Metrics abound, but few are comprehensive
- Metrics in use are absolute.
- Commonly used RMS error is seriously flawed:
 - It's very **pessimistic**:
 - If all 100 errors are 1 except for one term of 1000, then RMSE≈100
 - What's RMSE of a filter if it diverges on one or few of many runs?
 - It has **no** clear physical interpretation:
Is it "distance" between estimatee and estimate? **No!**
- **Conclusion**:
Alternative metrics and better understanding are needed.

Absolute Metrics vs. Others

Error Metric	Good for Evaluation of
Absolute	Estimation system
Relative	Estimation algorithm
Frequency count	Hit-or-miss type application

- Metrics in use are **absolute**, don't meet diverse needs.
- We have presented two other classes of metrics:
relative error metrics and frequency counts.

See: *IEEE Trans. AES*, 42(4):1340–1358, Oct. 2006

Incomprehensive Measures: Summary

Metric	Classification	Pros	Cons	Good for
RMSE, relative RMSE, AEE, relative AEE	pessimistic	popular, nice properties strong tie with MSE and s.d. clear physical interpretation, nice properties	large-error dominance, unclear physical interpretation	probabilistic analysis
HAE, relative HAE	optimistic	robust w.r.t. large error, nice properties	large-error prevalence small-error dominance, not popular, unclear physical interpretation	measuring average error averaging rates with a fixed base, measuring/comping good performance
GAE, relative GAE, median, mode	balanced	robust w.r.t. extreme error, nice properties	not popular	averaging ratios
RMSE, AEE, HAE, GAE, median, mode	absolute	robust w.r.t. extreme error	hard to find or manipulate	measuring typical error
relative RMSE, AEE, HAE, GAE, median, mode	relative	more popular	scenario sensitive	evaluating performance of estimation systems
BEEQ	relative, balanced	robust w.r.t. prior/prediction error, clear interpretation	depend on prior/prediction and measurement errors	comparing/evaluating performance of estimators
EMER	relative, balanced	robust w.r.t. measurement error, clear interpretation	depend on measurement error	comparing/evaluating improved performance of Bayesian estimators
BERF	relative, balanced	robust w.r.t. scenarios, nice properties	depend on prior/prediction error	comparing/evaluating classical estimators
success rate	relative, optimistic	robust w.r.t. measurement error, clear interpretation	not popular, unclear physical interpretation	improvement over meas. comparing/evaluating performance of Bayesian estimators
failure rate	relative, pessimistic	more comprehensive, clear interpretation	depend on prior/prediction error	comparing/evaluating bad performance
concentration probability	relative		concentration region sensitive	hit-or-miss type of application

Classification of Metrics

A performance metric is

- **Pessimistic** if it pays more attention to **bad performance** in that it consistently **underestimates** the performance (e.g. dominated by **large** errors)
- **Optimistic** if it pays more attention to **good performance** in that it consistently **overestimates** the performance (e.g., dominated by **small** errors)
- **Neutralistic** if it's neither pessimistic nor optimistic
- **Balanced** if its good performance and bad performance are accounted for in a balanced manner

The same concept applies to many other cases, e.g., **estimators, trackers, fusers, and credibility measures.**

Challenge 1: Comprehensive Evaluation

- Metrics in wide use are narrowly focused
- They are not fair, not good for performance ranking or comparison
- Our solutions:
 - **Error spectrum**: aggregate most error metrics so far (Daum Tribute, May 2007)
 - **Desirability metrics** w.r.t. a **desired** error density (Daum Tribute, May 2007)
 - **Concentration measures** w.r.t. a reference density (Fusion'07)

Error Spectrum

Let $e = \|\tilde{x}\|/\|x\|$ or $\|\tilde{x}\|$ of estimation error $\tilde{x}$. **Error spectrum** is

$$S(r) = S_e(r) = [E(e^r)]^{1/r}, \quad r \in [-\infty, \infty]$$

as a function of r . The lower $S(r)$ curve is the better.

The most useful portion of the curve is: $-1 \leq r \leq 2$.

- $S(2) = \text{RMSE}$, $S(1) = \text{AEE}$, $S(0) = \text{GAE}$, $S(-1) = \text{HAE}$
- $\min\{e_i\} = S(-\infty) \leq S(r) \leq S(\infty) = \max\{e_i\}$
- $S(r)$ is increasing with r : $S(r) < S(s)$ if $r < s$
- $S_e(r)$ is linearly homogeneous in e : $S_{\alpha e}(r) = \alpha S_e(r)$, $\forall \alpha > 0$
- $S_e(r)$ is monotonic in e : $S_e(r) \leq S_{e'}(r)$ if $e_i \leq e'_i$, $\forall i$
- $S_e(r)$ is invariant if e_i are permuted w.r.t. i
- $S_e(r)$ is strictly convex in e for any fixed $r > 1$
- $S_e(r)$ is strictly concave in e for any fixed $r < 1$

Challenge 2: Evaluation without Knowing Truth

- All existing metrics rely on knowing the ground truth
- Can we develop a performance evaluator that
 - Is comprehensive, systematic, generally applicable
 - **Doesn't need to know the ground truth?**
- I thought the answer is NO for years
- **Fortunately, I was wrong!**

Evaluation with Unknown Ground Truth

- Given:
 - True data set $z_1, \dots, z_N$, but don't know how it was generated
 - Assumed (not the true) data model: $z \sim \hat{f}(z|x)$ or $z = \hat{h}(x, v)$
- For each data point z_i , obtain estimate $\hat{x}_i$
- Use the estimate and assumed model to generate mock data set $\hat{z}_{i1}, \dots, \hat{z}_{iM}$:
 - draw from $\hat{f}(z|\hat{x}_i)$ or
 - generated by $\hat{z}_{ij} = \hat{h}(\hat{x}_i, v_{ij})$
- Measure distance between true data and mock data

$$d(z, \hat{z}) = \frac{1}{N} \sum_{j=1}^N d(z_i, \hat{z}_i), \quad d(z_i, \hat{z}_i) = \frac{1}{M} \sum_{j=1}^M d(z_i, \hat{z}_{ij})$$

Major Advantages of New Approach

- Comprehensive
- Generally applicable
- No need to know the ground truth
- Accounts for model mismatch as well as estimation error
- Discourages either overfitting or underfitting

See: ONR-GTRI Workshop on Tracking and Sensor Fusion, May 2007

Challenge 3: Performance Ranking

- How to rank performance of estimators?
- Rank them according to same measure
- Let them compete with each other: efficient
- We have developed (Fusion'07):
 - Relative loss: quantify how much one loses to other
 - Relative gain: quantify how much one gains over other
- Problem: transitivity may not hold
- Many other ways are possible
- Analogy: rank athlete performance

Summary

- Three challenges: comprehensive metric, unknown truth, performance ranking
- Existing methods known to us
 - Are incomprehensive, absolute,
 - Rely on knowing the ground truth, or
 - May ignore crucial coupling b/t estimate and estimatee
- A **general** approach to **comprehensive** evaluation of estimation performance **without knowing the ground truth** is possible
- Such an approach is outlined here
- Measure is not the only yardstick for performance ranking
- Rank by outcomes of competition

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Challenges and Recent Advances in Estimation Performance Evaluation^{*}

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Outline. Limitations of existing metrics. Challenge 1: Comprehensive evaluation. Challenge 2: Evaluation with unknown ground truth. Challenge 3: Alternative ranking of performance. Summary.

1 Existing Metrics' Limitations, Alternative Metrics, and Classification of Metrics

Limitations of existing metrics. While performance metrics for target tracking abound, there are only a few for estimation, especially widely used ones. These metrics have the following limitations in common: They are not comprehensive in scope; they need (complete) knowledge about the ground truth; they are sensitive to scenarios of evaluation.

Almost all evaluations of estimation performance are centered on the so-called root-mean-square error (*RMSE*), although it is more controversial as to which measures are better for estimator comparison (see, e.g. [1]). *RMSE* is seriously flawed: (a) It is very pessimistic: If all 100 errors are 1 except for one term of 1000, then $RMSE \approx 100$. What is the *RMSE* of a filter if it diverges on one or few of many runs? (b) It has no clear *physical* interpretation, although it has a clear probabilistic interpretation. Many practitioners confuse *RMSE* with the distance between estimatee (quantity to be estimated) and estimate in our physical world. Unfortunately, this is not the case. Therefore, alternative metrics and better understanding are needed. As elaborated in [3], the widely used *RMSE* should be replaced by some other measures of performance in many cases.

Absolute error metrics, relative error metrics, and frequency counts. Virtually all existing metrics in use are *absolute* in that they are not with respect to any reference and thus depend critically on the evaluation scenario, including estimatee magnitude, data accuracy, and possibly accuracy of prior information. As such, their use for performance evaluation is justified for an entire estimation *system* (including an estimation algorithm, a measurement subsystem, and others) but not for an estimation *algorithm* per se. This exemplifies its insufficiency to address diverse needs. Instead, relative error metrics are much more suitable for evaluation of an estimation algorithm. Three classes of alternative measures were proposed in [3]: (a) *absolute error metrics*, including average Euclidean error (AEE), geometric average error (GAE), harmonic average error (HAE), median and mode of error norm; (b) *relative error metrics*, including Bayesian estimation error quotient (BEEQ), estimate-measurement error ratio (EMER), Bayesian error reduction factor (BERF), and relative *RMSE*, AEE, GAE, HAE, median, and mode; and (c) *frequency counts*, including success rate, failure rate, and concentration probability.

These three classes of metrics differ in domain of application and each is best for a variety of situations, as outlined in the next table. Individually, they also have their own pros and cons and serve different purposes. A table is available in [3] that summarizes pros and cons and intended applications of each and every one of these metrics.

Error Metric	Good for Evaluation of
Absolute error metrics	Estimation system
Relative error metrics	Estimation algorithm
Frequency count	Hit-or-miss type application

Classification of metrics. To help better understand existing metrics and metrics to come, the following classification was proposed in [3] and made precise in [5]. A performance metric is *pessimistic* if it pays more attention to bad performance in that it consistently underestimates the performance (e.g. if it is dominated by large errors); *optimistic* if it pays more attention to good performance in that it consistently overestimates the performance; *neutralistic* if it's neither pessimistic nor optimistic; and *balanced* if its good performance and bad performance are accounted for in a balanced manner. The same concept applies to many other matters, e.g., classification of estimators, trackers, fusers, and credibility measures [4].

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[†]Target tracking relies on estimation, but tracking has its own issues. Estimation is in the core of data fusion, although each includes components not covered by the other. Although we choose to deal with estimation performance directly and explicitly here, what is presented addresses tracking and data fusion performance indirectly. In other words, we are actually talking about issues common to estimation, tracking, and data fusion performance evaluation.

2 Challenge 1: Comprehensive Evaluation of Performance

Metrics in wide use such as RMSE have a narrow focus. They are not fair nor good for performance ranking or comparison. To alleviate this problem, several more comprehensive metrics have been proposed in four classes: (a) error spectrum, which aggregates most error metrics available; (b) desirability metrics, which measure how close the actual error is to a desired error density; (c) concentration measures, which quantify how concentrated the errors are w.r.t. a reference density; and (d) the comprehensive estimation performance evaluator of the next section, which does not need to know the ground truth.

Error spectrum. Let $e = \|\tilde{x}\|$ or $e = \|\tilde{x}\|/\|x\|$ be the absolute or relative estimation error norm. The **error spectrum** (ES) introduced in [5] is defined as

$$S(r) = S_e(r) = [E(e^r)]^{1/r}$$

ES has a large array of nice properties important for performance evaluation, including (a) it aggregates many of the above metrics (e.g., $S(2) = \text{RMSE}$, $S(1) = \text{AEE}$, $S(0) = \text{GAE}$, $S(-1) = \text{HAE}$, $S(\infty) = \max e$ and $S(-\infty) = \min e$); (b) $\min e \leq S(r) \leq \max e$; (c) $S(r)$ is strictly increasing with r ; (d) $S_e(r)$ is monotonic and linearly homogeneous in e ; (e) $S_e(r)$ is invariant w.r.t. any label system for e ; and (f) $S_e(r)$ is strictly convex in e for any fixed $r > 1$ and strictly concave in e for any fixed $r < 1$.

It turns out that [5] error spectrum $S(r)$ is *pessimistic* if $r > 0$, *optimistic* if $r < 0$, and *balanced* if $r = 0$; the (absolute and relative) RMSE, AEE, and the failure rate are pessimistic; the (absolute and relative) HAE and success rate are optimistic; the (absolute and relative) GAE, median error, error mode, and the BEEQ, EMER, and BERF are neutralistic.

Desirability measures. They measure closeness between the actual error density $f(\cdot)$ and desired error density $f_d(\cdot)$. Several closeness measures have been proposed based on the correlation coefficient, Wasserstein metric, Kullback-Leibler information [6], and total variation distance. For example, the one based on the correlation coefficient, called **desirability level** [5] is defined as $\rho(0)$, where

$$\rho(u) = \frac{\int f_d(\tilde{x} + u)f(\tilde{x})d\tilde{x}}{[\int f_d(\tilde{x} + u)^2d\tilde{x} \int f(\tilde{x})^2d\tilde{x}]^{1/2}}$$

It has some nice properties, including positive definiteness, invariance under invertible affine transformations, and having the standard range: $0 \leq \rho(0) \leq 1$.

Concentration measures. They quantify concentration of the actual error relative to a reference distribution [7]. One of them, called **relative concentration index** (RCI), is defined as $\text{RCI} = E[f_r(\tilde{x})|f] / E[f_r(\tilde{x})|f_r]$, where f and f_r are the actual and reference error densities, respectively. These measures have some nice properties and can also serve as measures for performance comparison. For example, a distribution is more concentrated than the reference if and only if $\text{RCI} > 1$.

3 Challenge 2: Evaluation with Unknown Ground Truth

Most, if not almost all, people believe that performance evaluation cannot be done *without knowing the ground truth*. How would we know how large the estimation error is without knowing the truth? Indeed, all existing metrics developed so far rely on this knowledge. Computer simulation based performance evaluation can largely get by with this limitation. It, however, does pose a serious challenge for other types of studies, especially those using real-world data, in which case we struggle to come up with an accurate enough knowledge of the ground truth. Everyone who did such a study should have this experience.

A grand challenge is then: Is it possible to evaluate performance without the need to know the ground truth? Even better, can this be done comprehensively, systematically, and with general applicability? Most people think it impossible. Fortunately, this is not the case!

Comprehensive estimation performance evaluator (CEPE). Here is a concrete evaluator that makes the above dream come true [2]: (a) Given true data set $z_1, \dots, z_N$ without knowledge of how it was generated, and assumed (not necessarily correct) data model: $z \sim \hat{f}(z|x)$ or $z = \hat{h}(x, v)$. (b) For each data point z_i , obtain estimate $\hat{x}_i$. (c) Use the estimate and the assumed model to generate mock data set $\hat{z}_{i1}, \dots, \hat{z}_{iM}$: draw from $\hat{f}(z|\hat{x}_i)$ or generated by $\hat{z}_{ij} = \hat{h}(\hat{x}_i, v_j)$. (d) Measure distance between the true data and the mock data

$$d(z, \hat{z}) = \frac{1}{N} \sum_{j=1}^N d(z_i, \hat{z}_i), \quad d(z_i, \hat{z}_i) = \frac{1}{M} \sum_{j=1}^M d(z_i, \hat{z}_{ij})$$

A more powerful version of this evaluator particularly good for state estimation has also been developed.

Major advantages. It is comprehensive, systematically, and generally applicable; it does not need to know the ground truth; it accounts for model mismatch as well as estimation error; it discourages either overfitting or underfitting.

4 Challenge 3: Alternative Ranking of Performance

Given multiple estimators, how do we rank their performance? A commonly used approach is to rank them according to the same measure of performance. This is natural and most people stick to it thinking there are no viable alternatives.

In fact, to determine their ranking, we may let them compete with one another [1]. This alternative is distinctive in its high efficiency. While ranking based on a common performance measure depends only on information that is “marginal” of each estimator, this alternative uses directly “joint” or relative information of the multiple estimators. One may argue that usually a single estimator is used in an application and so the joint or relative information of the multiple estimators should not play any role in performance evaluation. To answer this criticism, consider the analogy of selecting a capable person for a challenging task by an IQ contest. Here the winner will also have to accomplish the task *alone*, yet selection by a contest is sensible and in fact common practice. The rationale lies largely in the high efficiency of this alternative.

In view of the above, we have developed [7] several measures in this category, including the *relative loss measure*, which quantifies how much worse whenever one estimator loses to the other, and the *relative gain measure*, which quantifies how much better whenever one estimator beats the other, both over many pairwise competitions.

A problem with these measures is that transitivity does not hold in general (e.g., A beats B and B beats C does not guarantee A beats C). Another rich class of alternative measures in the same spirit is under development. It appears that many of them can guarantee transitivity. Study of other alternatives is worthwhile and actually overdue. Here it is certainly beneficial to consider the analogy of ranking performance of athletes.

5 Summary

Existing methods and metrics for estimation performance evaluation have serious limitations. They are narrowly focused, overly pessimistic, hyper sensitive to evaluation scenario, totally reliant on knowing the ground truth, and may ignore crucial coupling between the estimate and estimatee.

Three challenges have been articulated: development of a comprehensive metric of estimation performance, evaluation of estimation performance without the need to know the ground truth, and development of alternative methods and measures for estimation performance ranking.

A general approach to comprehensive evaluation of estimation performance without the need to know the ground truth is possible. Such an approach has been developed and is outlined here.

Various metrics in three classes have been proposed recently: absolute metrics, relative metrics, and frequency counts. Having distinctive pros and cons, they should take over the widely used RMSE in many cases.

Three other classes of metrics have been developed: error spectrum, desirability metrics, and concentration measures. They are much more comprehensive than existing ones.

The use of a common performance measure is not the only yardstick for performance ranking. Alternatives do exist and may prove superior. A viable one is to rank by outcomes of competitions among estimators. Two measures in this category have been proposed and a third class is under development.

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"Global" Performance MOEs for Multitarget Tracking

Panel on Issues and Challenges in Performance Assessment of Multitarget Tracking Algorithms with Applications to Real-World Problems

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The Position Advocated in this Presentation

- **"Lumpy pillow" syndrome in performance estimation:**
 - multitarget tracking algorithms are highly nonlinear
 - improving performance with respect to one "local" measure of effectiveness (MoE) can result in decreasing performance with respect to another
- **Comprehensive multitarget tracking performance estimation must be based on the fundamental multitarget statistics of a given tracking problem**
- **This presentation:**
 - "global" information-theoretic MoEs:
 - measure *total performance* of a multitarget tracker using fundamental multitarget statistics
 - "semi-global" multitarget miss-distances
 - less comprehensive but more intuitively appealing

Multi-Object Csiszár Discrimination

Mahler (1997)

- determine "global" MoEs for multitarget fusion algorithms
- based on Csiszar information-discrimination "distances"

$$K_c(f, f_0) = \int f_0(X) c \left(\frac{f(X)}{f_0(X)} \right) \delta X$$

Labels in diagram: convex kernel, multi-track density function for tracker output, multi-object integral, ground truth reference multi-target density function.

Multi-Object Kullback-Leibler Discrimination

Mahler (1997)

- special case: $c(x) = x \cdot \log x$
- well-known information-theoretic measure of effectiveness

$$K_c(f, f_0) = \int f(X) \log \left(\frac{f(X)}{f_0(X)} \right) \delta X$$

$$\cong -\log(L \cdot f(\mathbf{g}_1, \dots, \mathbf{g}_n))$$

Labels in diagram: smallest-resolution factor, ground-truth tracks.

Multi-Object Miss-Distance

Drummond (1992-1995)

- first attempt to devise multi-object miss-distance
- based on intuitive optimal-assignment concept
- involves heuristic choices when no. of tracks $\neq$ no. of truths

$$d(X, Y) = \left(\min_{\sigma} \sum_{i=1}^n d(\mathbf{x}_i, \mathbf{y}_{\sigma(i)})^2 \right)^{1/2}$$

Labels in diagram: m ground truth targets, X; miss distance between X, Y?; n tracks, Y.

Wasserstein Multi-Object Miss-Distance

Hoffman and Mahler (2002)

- a multi-object miss distance that rigorously generalizes Drummond's optimal-assignment approach
 - larger values of p : target number errors more "penalized"

$$d_p(X, Y) = \left(\inf_C \sum_{i=1}^n \sum_{j=1}^m C_{ij} \cdot d(\mathbf{x}_i, \mathbf{y}_j)^p \right)^{1/p}$$

Label in diagram: infimum taken over all "transportation matrices" C

Optimal Subpattern Assignment (OSPA) Miss-Distance

Schuhmacher, Vo, and Vo (2008)

- discovered counter-intuitive behaviors of Wasserstein distances
- devised a more rigorous (and more computable) extension of Wasserstein distance that corrects these misbehaviors

$$d_{p,c}(X,Y) = \left(\min_{\sigma} \frac{1}{\max\{m,n\}} \sum_{i=1}^{\min\{m,n\}} \min\{x_i, d(x_i, y_{\sigma(i)})^p + c^p \cdot |m-n|\} \right)^{1/p}$$

minimum taken over all permutations σ on $1, \dots, \min\{m,n\}$

“Global” Performance MOEs for Multitarget Tracking

Position Paper: Panel on Issues and Challenges in Performance Assessment of Multitarget Tracking Algorithms with Applications to Real-World Problems

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Traditionally, performance analysis of multitarget data fusion algorithms has been based on measures of effectiveness (MOEs) that quantify “local” aspects of performance: probability of target detection, average localization miss distance, probability of correct ID, etc. Because multitarget tracking algorithms are highly nonlinear, improving performance with respect to one local MOE can result in decreasing performance with respect to another—and thus conflicting MOEs. Because of such problems, attempts have been made to construct over-all (“global”) MOEs via, for example, heuristic weighted averages of local MOEs. Unfortunately, this approach suffers from its own difficulties. The resulting single MOEs have tended to be arbitrary, non-intuitive, difficult to interpret, and sometimes not even invariant with respect to a change of units of measurement.

This position paper argues that comprehensive multitarget tracking performance estimation must be based on the fundamental multitarget statistics of a given tracking problem, as described by the theory of finite-set statistics.⁵ Specifically, truly comprehensive MOE should be defined in terms of the *multitarget Bayes posterior probability distribution* that characterizes the problem. I briefly survey the most promising techniques: multitarget Kullback-Leibler MOEs and multitarget Csisár *information-theoretic MOEs*. I also survey intermediately comprehensive MOEs: the *multitarget miss distances*.

Comprehensive multitarget MOEs can be defined in terms of information theory. Let $f_{k|k}(X)$ be the multitarget probability distribution describing the output of a multitarget tracking algorithm. Then the family of *multitarget Csisár discrimination MOEs* is defined by

$$I^c(f, g) \triangleq \int f_0(X) \cdot c\left(\frac{f_{k|k}(X)}{f_0(X)}\right) \delta X \quad (1)$$

where $f_0(X)$ is a multitarget reference density and where $c(x) \geq 0$ is a convex kernel function, i.e., $c(1) = 0$ and $c(x)$ is strictly convex at $x = 1$. Examples are $c(x) = x \cdot \log x$ and $c(x) = (\sqrt{x} - 1)^2$ and $c(x) = (x - 1)^2$. If we choose the first of these and let $f_0(X) = f_{\text{Grnd}}(X)$ model ground truth $\mathbf{g}_1, \dots, \mathbf{g}_\gamma$, then we get

$$K(f_{k|k}, f_{\text{Grnd}}) = \int f_{k|k}(X) \cdot \log\left(\frac{f_{k|k}(X)}{f_{\text{Grnd}}(X)}\right) \delta X \cong -\log L^{-1} f_{k|k}(\{\mathbf{g}_1, \dots, \mathbf{g}_\gamma\}) \quad (2)$$

where L is the (hyper)volume of the smallest degree of localization resolution that is desired for the given problem. Such MOEs were introduced in Chapter 8 of *Mathematics of Data Fusion*.³ They have been used to develop MOEs for multitarget tracking algorithms, for sensor management algorithms, and other applications.^{2,7,10,1,6,9}

Another type of MOE is not as comprehensive as information-theoretic MOEs, but is in some ways more intuitively accessible. These are the *multitarget miss distances*. Hoffman and Mahler⁴ introduced the family of

Wasserstein distances. Let $X = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ and $Y = \{\mathbf{y}_1, \dots, \mathbf{y}_m\}$ where $|X| = n$ and $|Y| = m$. Then the Wasserstein distance of power p is defined by

$$d_p(X, Y) \triangleq \inf_C \sqrt[p]{\sum_{i=1}^n \sum_{j=1}^m C_{i,j} \cdot d(\mathbf{x}_i, \mathbf{y}_j)^p} \quad (3)$$

where the infimum is taken over all $n \times m$ so-called “transportation matrices” C . The larger the value of p , the more that $d_p^W(X, X')$ penalizes deviations in target number.

Recently, Schuhmacher, Vo, and Vo⁸ have uncovered a number of deficiencies in the Wasserstein distances when used for assessing the performance of multitarget tracking algorithms. In response, they have devised closely related but even more theoretically and practically justifiable multitarget miss distances called the *optimal sub-pattern assignment* (OSPA) distances. Let $c > 0$. If $n \leq m$ these are defined by

$$d_p^c(X, Y) \triangleq \sqrt[p]{\min_{\sigma} \frac{1}{m} \sum_{i=1}^n \min\{\mathbf{x}_i, d(\mathbf{x}_i, \mathbf{y}_{\sigma i})^p + c^p \cdot (m - n)\}} \quad (4)$$

where the minimum is taken over all permutations σ on $1, \dots, m$. If $n \geq m$ then $d_p^c(X, Y) \triangleq d_p^c(Y, X)$.

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Issues and Challenges in Performance Assessment of Multitarget Tracking Algorithms with Applications to Real-World Problems

How Useful Are the Theoretical Bounds in the Real-World?

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Theoretical Performance Bounds

- Quantify analytically the best estimation/tracking accuracy achievable by **any** tracker
- Done even before the first measurement is received
- Independent of particular measurement values and track estimates
- Can be done offline
- Example: Cramer-Rao lower bound (CRLB), Weiss-Weinstein bound (WWLB), Bhattacharya bound,
- The performance limit given by these is a bound and **not the** bound

2

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MTT in the Real-World

- Multiple heterogeneous targets
- Multiple heterogeneous sensors
- Distributed, hierarchical, networked-systems
- Kinematic and non-kinematic data
- Target birth, spawning, death (time-varying)
- Target maneuvers, time-varying models
- Data association uncertainties
- Bias, location uncertainties, non-Gaussian noise
- Data feedback, fusion, data incest, correlation
- Communication issues, bandwidth limitations
- Data access privileges, reporting responsibilities
- Sensor management issues
- Lack of ground truth, false ground truth
- Fault tolerance, redundancy
- Data of non-quantifiable accuracy (e.g., HUMINT)
- ...

3

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Theoretical Performance Bounds

- Do not consider most of the above.

4

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Then Why Bother with Bounds*?

- Bounds provide an objective (sometimes subjective) achievable performance limit in (at least, simple) tracking problems
- Can serve as a baseline performance evaluation mechanism before trying the algorithms on more complex scenarios
- Useful for "what-if" calculations before deploying sensor assets
- Provide an MOP for resource management strategies
- A measure of confidence in the absence of filter calculated values
- A tool for testing trackers, estimates, covariances

5

*"To publish papers" is not a valid answer.

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Current State-of-the-Art in Bounds

- Cramer-Rao Bound for parametric estimation with measurement origin uncertainty (single target)
- Posterior CRLB for recursive state estimation for nonlinear non-Gaussian systems with single target
- PCRLB for multiple targets with measurement origin uncertainty (with some approximations)
- PCRLB for multiple sensors with centralized fusion
- Weiss-Weinstein bounds for handling discrete and continuous uncertainties (e.g., maneuvers)
- Recursive formulations for WWLB with maneuvering targets, time-varying number of targets
- Incorporation of feature/class information into PCRLB/WWLB

6

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Some Demonstrated Applications

- Sonobuoy management for multitarget tracking (with PCRLB)
- Maneuvering ground target tracking (with WWLB)
- Tracking and sensor management with multistatic sonar (with PCRLB)
- Closely-spaced target tracking with monopulse radar (with PCRLB)
- DOA tracking with multiple targets (with PCRLB)
- Sensor management in decentralized architectures
- UAV management
- Geolocalization with DOA/TDOA measurements
- Missile tracking problems
- Use of bounds when filter-calculated covariances are not available

7

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Some Issues

- Bounds are evaluated at truth (use estimates when truth is not available in the real-world)
- Bounds may not be meaningful if estimates are not good (similar to the divergence problem in EKF)
- High computational complexity (with PCRLB and, especially, with WWLB)
- Cannot easily handle many fusion issues (e.g., correlation, feedback, data incest)
- Cannot easily handle distributed, networked, hierarchical architectures without approximations

8

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Some Challenges

- Bounds that are computationally efficient in large-scale real-world tracking problems
- Finding bounds that are effective with long-term prediction and track estimates
- Bounds that can handle discrete and continuous uncertainties efficiently
- Bounds for common fusion architectures
- Bounds for higher levels of fusion (e.g., classification, intent)
- Bounds for common data association mechanisms (e.g., assignment, multiframe)
- Make bounds understandable for operators
- Quantify when these bounds break down

9

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Thank you.

10

Issues and Challenges in Performance Assessment of Multitarget Tracking Algorithms with Applications to Real-World Problems: How Useful Are the Theoretical Bounds in the Real-World?

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ABSTRACT

A number of performance bounds like, for example, Cramer-Rao Lower Bound and Weiss-Weinstein Bound, have been derived to quantify the performance achievable by any algorithm in state estimation problems. These bounds are evaluated at the ground truth, which means that the exact bound is available only for simulation-based or instrumented real experiments. Also, a number of assumptions on the statistics, state models and their evolution over time are made in order to facilitate the derivation of these complex bounds. As a result, these bounds are at best approximations of achievable performance. In addition, these bounds are often computationally cumbersome, if at all possible, to evaluate in realistic multisensor-multitarget tracking problems. In spite of these limitations, the bounds have been used successfully for performance prediction, tracker evaluation and sensor resource management. In this short paper, we briefly discuss the usefulness of theoretical bounds as realistic performance evaluation measures in real-world tracking problems.

Keywords: Multisensor-multitarget tracking, estimation algorithm, performance evaluation, performance bounds, Cramer-Rao lower bound, Weiss-Weinstein bound

1. INTRODUCTION

Multisensor-multitarget tracking in the real-world involves a multitude of aspects like, for example, sensor calibration, signal processing, data association, state estimation, performance evaluation, sensor resource management and computational issues [1][2]. That is, tracking is not synonymous with state estimation, but rather it subsumes the latter. A critical, but often neglected, component in tracking is performance evaluation. While it is easy to make a tracker work well and look good on a particular tracking problem and on a particular scenario, it is challenging to make it work uniformly well on most tracking problems. In view of this, there exists an urgent need not only to specify meaningful performance metrics, but also a complete performance evaluation framework with benchmark scenarios. As in many other fields of research, in order to address the issue of impartial evaluation of trackers, different benchmark problems have been proposed for tracking problems as well. In spite of their limited scope, these benchmark problems have been very effective in comparing and contrasting different tracking algorithms in terms of their tracking accuracy, computational complexity and other aspects like sensor usage.

Another common way to evaluate trackers has been the use of theoretical performance metrics like lower bounds on state estimation errors [4]-[9]. These lower bounds quantify the performance achievable by *any* tracker on a particular scenario. Some of the commonly used theoretical bounds include Cramer-Rao lower bound (CRLB), Weiss-Weinstein lower bound (WWLB) and Bhattacharya bound. These bounds can be calculated off-line, even before the first measurement is received. Also, they are independent of particular measurement values and track estimates. That is, the underlying tracker mechanism does not affect the bound. These properties make the bounds attractive in tracking problems as a way to quantify expected tracking performance. On the other hand, there are a number of shortcomings that may render the bounds useless in realistic tracking problems with real-world issues [3]-[9]. For example, theoretical bounds are to be evaluated at true values of target state, which is often not available in real-world problems. The use of estimated values does not result in meaningful performance limits. In the following, we discuss the practical value of these bounds in realistic target tracking problems.

2. TARGET TRACKING IN THE REAL-WORLD

While the classical single-target-in-a-clean-environment scenario is common in many academic publications, target tracking in the real-world consists of a number of challenging issues. Some of these issues are listed below:

- Multiple heterogeneous targets
- Multiple heterogeneous sensors
- Distributed, hierarchical, networked-systems
- Kinematic and non-kinematic data
- Target birth, spawning, death (time-varying)
- Target maneuvers, time-varying models
- Data association uncertainties
- Bias, location uncertainties, non-Gaussian noise
- Data feedback, fusion, data incest, correlation
- Communication issues, bandwidth limitations
- Data access privileges, reporting responsibilities
- Sensor management issues
- Lack of ground truth, false ground truth
- Fault tolerance, redundancy
- Data of non-quantifiable accuracy (e.g., HUMINT)

While it must be admitted that the theoretical bounds do not consider many of these issues, they serve the following useful purposes in tracking problems:

- They provide an objective (sometimes subjective) achievable performance limit in (at least, simple) tracking problems.
- They can serve as a baseline performance evaluation mechanism before trying the algorithms on more complex scenarios.
- They are useful for “what-if” calculations before deploying sensor assets.
- They provide a measure of performance (MOP) for resource management strategies.
- They are a measure of confidence in the absence of filter calculated values.
- They are a tool for testing trackers, estimates and covariances.

3. SOME ISSUES AND CHALLENGES

In spite of their effective use in many target tracking and fusion problems, theoretical performance bounds have some limitations that restrict their applicability to general tracking problems. We list some of those limitations below:

- Bounds are evaluated at truth, and estimates are used when truth is not available in the real-world.
- Bounds may not be meaningful if estimates are not good (similar to the divergence problem in EKF).
- Calculations of these bounds involved high computational complexity (with PCRLB and, especially, with WWLB).
- They cannot easily handle many fusion issues (e.g., correlation, feedback, data incest).
- They cannot easily handle distributed, networked, hierarchical architectures without approximations.

In view of these limitations, we suggest the following as possible challenges that need to be overcome in order to make theoretical performance bounds useful in realistic multisensor-multitarget tracking problems:

- Bounds that are computationally efficient in large-scale real-world tracking problems.
- Bounds that are effective with long-term prediction and track estimates.
- Bounds that can handle discrete and continuous uncertainties efficiently
- Bounds for common fusion architectures
- Bounds for higher levels of fusion (e.g., classification, intent)
- Bounds for common data association mechanisms (e.g., assignment, multiframe)
- Bounds that are understandable and useful for operators
- Breaking points of bounds.

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