**AFSL References**

This document contains a discussion of the various references located in the \\AFSL\TechnicalDataPackage\Word\AFSLReferences.xml file. This is designed to give broader context to these references and allow easy integration of these references into other documents.

# Artificial Intelligence

# Autonomous Systems

# Collision Avoidance

# Formation

Lum work in the Boeing VSTL lab [1].

# Graph Theory

# Hardware and Simulation

# Human Factors

# Insitu

# Magnetics

# Mapping and Geodesics

# Mathematics

# Miscellaneous

# Model Predictive Control

# Neural Networks

# Optimization

# Path Planning

# Probability Density Representations

# Risk for UAVs

## UW’s risk assessment model for UAS operations [2].

Paper that describes UW’s risk assessment model. This includes a brief discussion of the regulations, detailed derivation of the model, and three example scenarios of risk assessment.

## Monte Carlo risk assessment [3].

This paper describes a methodologies which can be used to assess the risk of UAS operation in potentially populated area. The model utilizes probability density function (PDF) and image-processed satellite imagery to give an accurate site-specific risk assessment.

## Estimate of Human Control Over Mid-air Collision [4]

First paper to approach estimating mid-air collision using random gas molecule collision model.

## System Level Airworthiness Tool: A Comprehensive Approach to Small Unmanned Aircraft System Airworthiness [5]

This paper describes a risk-based approach to analyze the safety of UAS operations. Authors developed a tool called System Level Airworthiness Tool (SLAT).

## Challenges to the Development of an Airworthiness Regulatory Framework for Unmanned Aircraft Systems [6] [7] [8]

These papers describe a risk assessment model that utilizes the barrier-bow-tie model to identify and manage risks associated with UAS operations.

## Assessing the Influence of Human Factors and Experience on Predator Mishaps [9]

A study that describes how risk factors for a specific UAS (Predator in this case) changes over time.

## Aerosonde Hazard Estimation [10]

Risk assessment of Aerosonde aircraft.

## Quantitative Risk Management as a Regulatory Approach to Civil UAVs [11]

This paper proposes quantitative risk management as a regulatory approach to civil UAVs.

## Safety Consideration for Operation of Unmanned Aerial Vehicles in the National Airspace System [12]

This paper performed risk analysis of UAS operation by combining the severity of the hazard and its likelihood of occurrence.

# Searching

# Sensor Nets and Groups

# Target Tracking

# Wildfires

UW paper using Australia Study Abroad 2014 data to detect wildfires with UAS [13]

# Mapping

UW paper using Australia Study Abroad 2015 data to investigate precision agriculture with a multi-spectral camera [14]

# Navigation and Sensor Fusion (JACTI 2015)

Bancroft and Lachapelle, Data Fusion Algorithms for Multiple Inertial Measurement Units [15]

1. Bancroft, J. B., & Lachapelle, G. (2011). Data Fusion Algorithms for Multiple Inertial Measurement Units. Sensors (Basel, Switzerland), 11(7), 6771–6798. <http://doi.org/10.3390/s110706771>
2. Nice introduction to Kalman filtered data streams
3. Paper focuses on fusing inertial measurement units
   1. Use a least squares fit to combine the inertial measurements
   2. End up with a non-linear model that is then linearized
4. Fault detection and exclusion (FDE)
   1. Flagged when “misclosure” or “innovation sequence” are zero mean
   2. FDE not suitable for their application of sensor arrays
5. Mention the Null and Alternate hypothesis (Kalman)
6. 21 state filters
   1. X, y, z position, angles, acceleration, etc??
7. Use Federated filters
   1. Developed in the 80’s and 90’s for combining GPS and INS data
      1. See Allertron and Jia, 2005.
   2. “typically four genres of sharing information: no reset, fusion reset, zero reset and cascaded”
   3. “Federated No Reset (FNR) and Federated Fusion Reset (FFR) are used herein as the other methods of sharing information are not conducive to inertial navigation systems”
   4. “rules of observation” violations with non-synchronous data??
   5. “The master fusion is performed via least squares with each local filter’s PVA providing the observations”
8. Full filter tuning was an overly burdensome task

Allerton and Jia, A review of multisensory fusion methodologies for aircraft navigation systems [16]

1. Allerton, D., & Jia, H. (2005). A Review of Multisensor Fusion Methodologies for Aircraft Navigation Systems. Journal of Navigation, 58(3), 405-417.
2. <http://alliance-primo.hosted.exlibrisgroup.com/UW:all:TN_cambridgesgmS0373463305003383>
3. Kalman filter based data fusion with fault tolerance
   1. Explicitly written as a guide for nav system designers 🡪 super useful!
4. Fault tolerance
   1. System level
      1. Often are majority voting or weighted mean combinations of data
      2. triple redundancy needed for voting
   2. Component (sensor) level
      1. Getting cheaper/lighter with microprocessors and embedded Kalman filters
      2. IMUs and skewed redundant IMU (SRIMU)
5. Data Fusion
   1. Centralized filter architecture
      1. Most common approach, theoretically the best
      2. See references 9 and 10 (centralized GPS/Doppler/INS data fusion)
      3. See references 11 and 12 (tightly-coupled GPS/INS)
   2. Cascaded Filter Architecture
      1. Great for linking multiple units with their own internal Kalman filters
      2. One challenge is that each subsystem may not output covariance information
      3. Look up reference 14 and 15!
      4. Accuracy of the cascaded system is dependent on the correlation of the data inputs, this could be a problem with the LAMS data where the heading and velocity data are closely correlated with the position data
      5. Ref 16 investigates GPS errors
   3. Federated filter Architecture
      1. Could use the LAMS as the “reference sensor” – see figure 7
         1. Problem is that the system is then susceptible to a single point of failure
      2. Benefit over centralized filer is improvements in failure detection, isolation and recovery (FDIR)
      3. Detriment is that the Federated filter is almost always sub-optimal with respect to the centralized filter
         1. FDIR gains are likely sufficient to offset this sub-optimal performance
   4. Distributed Filter Architectures
      1. State fusion
         1. Local filters 🡪 local state estimates 🡪 central filter 🡪 global state estimate
      2. Measurement fusion
         1. Subsets of measurements are fused with a bank of Kalman filters 🡪 multiple global state estimates 🡪 combine global state estimates

Hall & Llinas, Handbook of Multisensor Data Fusion [17]

1. Hall, D., & Llinas, James. (2001). Handbook of multisensor data fusion (Electrical engineering and applied signal processing series). Boca Raton, FL: CRC Press.
   1. Chapters 1, 7, and 9 look the most promising
   2. <http://dx.doi.org/10.1201/9781420038545>

Chapter 1

1. Basic intro
2. Three processing architectures
   1. Fusion of sensor data (e.g. interferometry, or averaging temperature sensor readings)
      1. Kalman filter is typically used
      2. THIS IS WHERE WE OPERATE
   2. Fusion of feature vectors (e.g. taste, smell, sight combined to build a picture of the object)
      1. Clustering, classification, or pattern recognition methods
   3. Fusion of high level inferences (e.g. IFFN, aircraft type, etc.)
      1. Weighted decision methods (voting techniques)
      2. Bayesian inference
      3. Dempster-Shafer’s method
3. “Single-target tracking in excellent signal-to-noise environments for dynamically well-behaved (i.e., dynamically predictable) targets is a straightforward, easily resolved problem.”
   1. Multi-hypothesis tracking (MHT), Random Set Theory (RST), etc. are advanced techniques for densely populated environments and highly maneuverable targets
      1. I.e. they are not suitable for JCATI 2015
4. “Data fusion has suffered from a lack of rigor with regard to the test and evaluation of algorithms and the means of transitioning research ﬁndings from theory to application.”
5. See: Hall, D. (1992). Mathematical techniques in multisensor data fusion (Artech House microwave library). Boston: Artech House.
   1. Available at Engineering Library Stacks-Floors 3&4 (TK5102.5 .H26 1992 )

Chapter 7

1. Contrasting Approaches to Combine Evidence
2. Probability theory is the historically accepted way, but it assumes an axiomatic definition of the underlying nature of the system it is applied to
   1. Fuzzy logic is similar, but differs in how it deals with unions and intersections of events
   2. Interval probabilities are another option for dealing with imprecise or incomplete information or disjoint sets of information
   3. “Given that…
      1. The degree of plausibility can be expressed by a real number,
      2. The extremes of the plausibility scale must be compatible with the truth values of logic,
      3. An inﬁnitesimal increase in the plausibility of statement A implies an inﬁnitesimal decrease in the plausibility of the statement not-A,
      4. The plausibility of a statement must be independent of the order in which the terms of the statement are evaluated,
      5. All available evidence must be used to evaluate plausibility, and
      6. Equivalent statements must have the same plausibility,
      7. …then the deﬁnition of a probability space follows as a logical consequence.12”
3. Probability spaces can change in subtle ways (example)
   1. Bayesian classifiers are unscalable when the probability space they are acting in changes
   2. Take home: be careful that your validation tests do not violate one of the underlying assumptions of the scheme you are testing
4. Bayes optimal data fusion
   1. Observation 🡪 measurement vector 🡪 minimize risk by threshold filtering a “likelihood ratio”
   2. “An important property of this test in any of its equivalent forms is its ability to optimally combine prior information with measurement information.”
5. Fuzzy logic not relevant to JACTI 2015
6. Dempster-Shafer belief theory is a possible alternative to probability theory for catching faulty data inputs
   1. Belief theory is not as good at generating results for clear-cut decisions
7. Article includes nice examples of each approach applied in parallel to data fusion problems
8. Continuous theme throughout paper: humans are bad at probability, its estimation, its significance 🡪 robust computer-based systems are necessary
   1. Situations where we are successful (global reasoning) suggest we should try organizing computational domains that mimic the human brain

Uhlmann, CI methods for fault-tolerant distributed data fusion [18]

1. Jeffrey K. Uhlmann, Covariance consistency methods for fault-tolerant distributed data fusion, Information Fusion, Volume 4, Issue 3, September 2003, Pages 201-215, ISSN 1566-2535, http://dx.doi.org/10.1016/S1566-2535(03)00036-8.
   1. <http://www.sciencedirect.com/science/article/pii/S1566253503000368>
   2. Abstract: This paper presents a general, rigorous, and fault-tolerant framework for maintaining consistent mean and covariance estimates in an arbitrary, dynamic, distributed network of information processing nodes. In particular, a solution is provided that addresses the information deconfliction problem that arises when estimates from two or more different nodes are determined to be inconsistent with each other, e.g., when two high precision (small covariance) estimates place the position of a particular object at very different locations. The challenge is to be able to resolve such inconsistencies without having to access and exploit global information to determine which of the estimates is spurious. The solution proposed in this paper is called Covariance Union.
   3. Keywords: Control; Convex optimization; Covariance Intersection; Covariance Union; Data fusion; Deconfliction; Distributed processing; Fault tolerance; Kalman filter; Network-centric; Network management; Semidefinite programming
2. Emphasis on distributed data processing systems
   1. Ideally the system incorporates all of the sensor input to produce a refined state estimate
   2. Ideally the system is free of feedback effects
3. Problem is that it is often impossible to build a complete and bounded Bayesian system so mathematical rigor is replaced by approximations and/or heuristics
4. This is unacceptable for safety-critical systems
5. Kalman Filter is the standard
6. It will give the best estimate of fused data
7. [Wikipedia] Used for Apollo guidance computer, ICBMs, cruise missiles, etc.
8. Kalman fails when data are NOT uncorrelated
9. Our data SHOULD be uncorrelated
   * 1. LAMS and GPS/ADS-B use independent methods to determine location and INS information
     2. Catch may be in the common coordinate transformations that are used when processing each type of data
10. The fusion rules shall ensure that the result is non-divergent!
11. E.g. the fused estimate can never be worse (equal is ok) than any of the piece-part estimates
12. This holds true over a time series of fusions as well
13. A single spurious estimate can corrupt the integrity of all system estimates
14. Specifically in distributed systems with message passing, but there is a similar possibility in centralized systems too
15. Must test for robust error handling and spurious data rejection
16. E.g. test for accelerations above some threshold, or (airspeed, NOT groundspeed) velocities above or below some fixed bounds for a given model of aircraft
17. Covariance Intersection 🡪 Covariance Union for conflicting data
18. Use Mahalanobis distance (**a** – **b**)T(**A** + **B**)-1(**a** – **b**)
19. This metric is large if covariances are small, but means do not agree
20. This metric is small if covariances are large, but means agree well
21. If the Mahalanobis distance is above some threshold then that is used to flag points that must be deconflicted using a Covariance Union
22. Because you don’t know WHICH point is spurious you must use a unioned estimate if you want to rigorously fuse the data
23. Benefit is that the fused estimate with larger covariance can be assimilated into future estimates that are also consistent
24. This is the meat and potatoes of the method: in distributed networks a single corrupt measurement may dramatically increase the covariance of neighboring nodes, but the result is still consistent and naturally decays away as more nodes combine their more accurate estimates with the spurious measurement
25. SO LONG AS THE FLAGGING THRESHOLD IS SET APPROPARIATELY IT IS IMPOSSIBLE TO PUSH THE POSITION ESTIMATE FAR AWAY FROM GROUND TRUTH WITHOUT CONTINUOUS <SLIGHTLY> CONFLICTING INFORMATION BEING INTRODUCED INTO THE SYSTEM
26. Another major benefit is that this method works for distributed systems with some feedback, so if we feed position data back into the ADS-B system then harvest that same data we will be insulated from data corruption
27. I.e. global information is not required to reset the system
28. From the Conclusion: “The CU approach is likely to ﬁnd uses in a broader range of applications in which mean and covariance estimates are maintained. Examples include almost any current application of the Kalman ﬁlter or CI, e.g., for control or tracking.”
29. That said, CI and the Kalman filer are “optimal for disjoint classes of problems” so their performance is not strictly comparable
30. I.e. CI is more conservative, so if the conditions necessary to utilize a Kalman filter are met (estimates are independent) it is detrimental to use CI
31. “Split CI” is equivalent to the Kalman filter when data are completely independent
32. CI should be utilized where estimates are partially or completely correlated

CI is the optimal method when two estimates are completely correlated

## Federal Aviation Administration. (2014, August 26). *Satellite Navigation - GBAS - How It Works*.

Retrieved from FAA.gov: <http://www.faa.gov/about/office_org/headquarters_offices/ato/service_units/techops/navservices/gnss/laas/howitworks/>

GBAS provided positional corrections and integrity measurements. The GBAS transmits a correction factor determined by the average error the ground reference stations (fixed positions determined by survey) have between their fixed position and their GPS provided position. GBAS avionics will only use GPS satellites for which it receives GBAS correction terms. GBAS is normally located at airports and has a broadcast radius of approximately 23 nautical miles. [19]

## Groves, P. D. (2013) Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems, Second Edition

An overview of a Kalman Filter Algorithm: [20]

1. Calculate the transition matrix
2. Calculate the system noise covariance matrix,
3. Propagate the state vector estimate from and
4. Propagate the error covariance matrix from and
5. Calculate the measurement matrix
6. Calculate the measurement noise covariance matrix
7. Calculate the Kalman gain matrix
8. Formulate the measurement
9. Update the state vector estimate from to
10. Update the error covariance matrix from to

## Houshangi, N.; Azizi, F., "Mobile Robot Position Determination Using Data Integration of Odometry and Gyroscope” [21]

1. The study relates to robot positioning information calculated using odometry
   1. Systematic and nonsystematic errors associated with odometry
      1. Systematic errors (different robot wheel diameters)
      2. Nonsystematic errors (wheel slippage on various surfaces)
2. Several methods have been used in attempts to correct odometry errors
   1. UMBark method, robot is run about a square path several times
      1. Final position and orientation errors are calculated
      2. Errors are used to derive correction factors which are used to more-accurately estimate the robot’s position
   2. Gyrodometry
      1. Robot’s position and orientation are calculated based on a combination of odometry (for level surface movement), and gyroscopic measurement (for travel over bumps and hills)
   3. Extended Kalman Filter
      1. Robot outfitted with triaxial gyro, triaxial accelerometer, and two electro-level tilt sensors
      2. Errors measured as exponentials w/ respect to time before EKF applied
      3. EKF improved the error on robot state estimation by a factor of 5
3. Research effort made use of Unscented Kalman Filter for inertial sensor and odometry and then compared these results to those generated with use of an Extended Kalman Filter
4. The experiment included a Pioneer 2-Dxe robot with a KVH E-core gyroscope with an input rate of +/- 30 degrees/sec and resolution of 0.014 degrees/sec
   1. Odometry information and gyro output are both read using a C++ program
   2. Matlab program used for UKF and EKF estimates of robot position
5. Experiment 1 Results
   1. Experiment tested effects of unequal wheel diameters on robot position/orientation by having lower pressure in left wheel than right wheel
   2. UKF results predicted robot heading within 0.65 degrees and maintained lowest error for robot positioning information
6. Experiment 2 Results
   1. Experiment tested effects of errors introduced by robot wheels sliding on surface
   2. UKF results closely matched gyro and EKF results for robot heading, but offered much better approximation of robot positioning information
7. Authors concluded that “the UKF estimates the robot’s position and orientation more accurately than the previously used approach of EKF”.
8. Details of Kalman Filter development/implementation in the Matlab code were not described within the research paper

## Julier, Uhlmann, “Unscented filtering and nonlinear estimation” [22]

1. The Extended Kalman Filter (EKF) is the most widely-used estimation algorithm for nonlinear systems, but it is notoriously difficult to tune and use
   1. Problems arise when nonlinear systems are “linearized” for use with the filter
   2. Unscented Kalman Filter (UKF) was developed in order to remedy these deficiencies
2. For a nonlinear system, methods must be used to approximate the predicted state and predicted observation. In a linear system these quantities are known and related through the linear Kalman Filter equations
3. Linearization fails most-noticeably when large errors are present in measurements (i.e. sonar applications with good range measurements but poor bearing measurements)
4. Unscented transformation is “founded on the intuition that it is easier to approximate a probability distribution than it is to approximate and arbitrary nonlinear function or transformation”
   1. Set of points are chosen such that their mean and covariance are known and are representative of the mean and covariance of the entire set
   2. The nonlinear function is applied to each of the points in the set which generates a set of transformed points
   3. The “statistics of the transformed points can then be calculated to form an estimate of the nonlinearly transformed mean and covariance”
5. The paper outlines several examples in order to highlight the differences between the results of a UKF and an EKF. The examples effectively show why a UKF is a useful, less-complex method than the EKF for filtering problems

## Beard, Ba-Tuong and Ba-Ngu, “Bayesian Multi-Traget Tracking with Merged Measurements Using Labelled Random Finite Sets” [23]

1. Most tracking algorithms assume that each target generates independent measurements
   1. Most real-world situations violate this assumption when targets overlap
2. Joint Probabilistic Data Association (JPDA) algorithm uses grid model for determining merge probability but requires a known number of targets
3. Random Finite Sets have been used for multi-target tracking purposes, but have been criticized for focusing on multi-target filtering instead of tracking
4. This seems useful if we need to separate targets that aren’t already identified with separate tracking identifiers

# Bibliography

|  |  |
| --- | --- |
| [1] | C. W. Lum, J. Vagners, M. Vavrina and J. Vian, "Formation Flight of Swarms of Autonomous Vehicles In Obstructed Environments Using Vector Field Navigation," in *Proceedings of the International Conference on Unmanned Aircraft Systems*, 2012. |
| [2] | C. W. Lum and B. Waggoner, "A Risk Based Paradigm and Model for Unmanned Aerial Systems in the National Airspace," in *Proceedings of the AIAA Infotech@Aerospace Conference*, St. Louis, 2011. |
| [3] | C. W. Lum, K. R. Gauksheim, J. Vagners and T. McGeer, "Assessing and Estimating Risk of Operating Unmanned Aerial Systems in Populated Areas," in *Proceedings of the AIAA Aviation Technology, Integration, and Operations Conference*, 2011. |
| [4] | J. Anno, "Estimate of Human Control Over Mid-Air Collisions," *Journal of Aircraft,* pp. 86-88, 1982. |
| [5] | D. Burke, "System Level Airworthiness Tool: A Comprehensive Approach to Small Unmanned Aircraft System Airworthiness," North Carolina State University, 2010. |
| [6] | R. A. Clothier, B. P. Williams and N. L. Fulton, "Structuring the safety case for unmanned aircraft system operations in non-segregated airspace," *Safety Science,* vol. 79, pp. 213-228, 2015. |
| [7] | R. A. Clothier, B. P. Williams, J. Coyne, M. Wade and A. Washington, "Challenges to the Development of an Airworthiness Regulatory Framework for Unmanned Aircraft Systems," Melbourne, 2015. |
| [8] | R. Clothier, B. Williams and A. Washington, "Development of a Template Safety Case for Unmanned Aircraft Operations Over Populus Areas," SAE International, 2015. |
| [9] | R. Herz, "Assessing the Influence of Human Factors and Experience on Predator Mishaps," Northcentral University, 2008. |
| [10] | T. McGeer, "Aerosonde Hazard Estimation," Aerovel Corporation, 1994. |
| [11] | J. Vagners, T. McGeer and L. Newcome, "Quantitative Risk Management as a Regulatory Approach to Civil UAVs," 1999. |
| [12] | R. E. Weibel and R. J. Hansman, "Safety Consideration for Operation of Unmanned Aerial Vehicles in the National Airspace System," MIT International Center for Air Transportation, Cambridge, 2005. |
| [13] | C. W. Lum, A. Summers, B. Carpenter, A. Rodriguez and M. Dunbabin, "Automatic Wildfire Detection and Simulation Using Optical Information from Unmanned Aerial Systems," in *Proceedings of the 2015 SAE Aerotec Conference*, Seattle, 2015. |
| [14] | C. W. Lum, M. MacKenzie, C. Shaw-Feather, E. Luker and M. Dunbabin, "Multispectral Imaging and Elevation Mapping from an Unmanned Aerial System for Precision Agriculture Applications," in *Proceedings of the 13th International Conference on Precision Agriculture*, St. Louis, 2016. |
| [15] | J. Bancroft and G. Lachapelle, "Data Fusion Algorithms for Multiple Inertial Measurement Units.," *Sensors,* vol. 11, no. 7, pp. 6771-6798, 2011. |
| [16] | D. Allerton and H. Jia, "A Review of Multisensor Fusion Methodologies for Aircraft Navigation Systems.," *Journal of Navigation,* vol. 58, no. 3, pp. 405-417, 2005. |
| [17] | D. Hall and J. Llinas, Handbook of multisensor data fusion (Electrical engineering and applied signal processing series)., Boca Raton, FL: CRC Press, 2001. |
| [18] | J. Uhlmann, "Covariance consistency methods for fault-tolerant distributed data fusion.," *Information Fusion,* vol. 4, no. 3, pp. 201-215, 2003. |
| [19] | Federal Aviation Administration, "Satellite Navigation - GBAS - How it Works," FAA.gov, 26 August 2014. [Online]. Available: http://www.faa.gov/about/office\_org/headquarters\_offices/ato/service\_units/techops/navservices/gnss/laas/howitworks/. [Accessed 15 September 2015]. |
| [20] | P. D. Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems, Second Edition, Boston: Artech House, 2013. |
| [21] | F. Azizi and N. Houshangi, "Mobile Robot Position Determination Using Data Integration of Odometry and Gyroscope," *Automation Congress,* pp. 1-8, 2006. |
| [22] | S. Julier and J. Uhlmann, "Unscented Filtering and Nonlinear Estimation," *Proceedings of the IEEE,* vol. 92, no. 3, pp. 401-422, 2004. |
| [23] | M. Beard, B.-T. Vo and B.-N. Vo, "Bayesian Multi-Target Tracking with Merged Measurements Using Labelled Random Finite Sets," *IEEE Transactions on Signal Processing,* vol. 63, no. 6, pp. 1433-1447, 2015. |
| [24] | C. W. Lum, J. Vagners, J.-S. Jang and J. Vian, "Partioned Searching and Deconfliction: Analysis and Flight Tests," in *Proceedings of the IEEE American Control Conference*, Seattle, 2010. |
| [25] | C. W. Lum, J. Vagners and R. T. Rysdyk, "Search Algorithms for Teams of Heterogeneous Agents with Coverage Guarantees," *AIAA Journal of Aerospace Computing, Information, and Communication,* vol. 7, no. 1, pp. 1-31, 2010. |
| [26] | E. D. McCormack, "The Use of Small Unmanned Aircraft by the Washington State Department of Transportation," Washington State Transportation Center (TRAC), Seattle, 2008. |