ESCAPE Data Collection for Multi-Modal Data Fusion Research

Peter Zulch, Marcello Distasio, Todd Cushman
Air Force Research Laboratory
Rome, NY 13440
peter.zulch, marcello.distasio,
todd.cushman@us.af.mil

Brian Wilson, Ben Hart
Michigan Tech Research Institute
Ann Arbor, MI
brwilson, behart@mtu.edu

Erik Blasch
AF Office of Scientific Research
Arlington, VA 22203
erik.blasch.1@us.af.mil

Abstract—**Over the last decade there has been a technological explosion of advanced, digital, solid state, software controlled, and low size, weight, power and cost (SWaPC) sensors and payloads. The sensor advancement allowed engineering practitioners the ability to easily perform a variety of remote sensing operations and consider a wide range of modalities measuring the environment simultaneously. However, there has not been a common multi-modal data set to compare data fusion methods. This paper describes a multi-mode data set performed by the Air Force Research Laboratory, Information Directorate, to enable multi-modal signature data-fusion research. The *Experiments, Scenarios, Concept of Operations, and Prototype Engineering* (ESCAPE) collection brings together electro-optical, infrared, distributed passive radio-frequency, radar, acoustic and seismic data in a common scenario for the application of advanced fusion methods for aerospace systems. The paper details hardware, scenarios, and data collection specifics. Scenarios involved disparate moving emitting ground vehicles, challenging vehicle path patterns, and differing vehicle noise profiles. The purpose of the data collection, and the resulting data sets, is to engage the data fusion community in advanced upstream heterogeneous data analytics, design, and understanding.**

TABLE OF CONTENTS

1. INTRODUCTION

Data sets, challenge problems, and baseline methods provide methods of comparison to advance research in sensor exploitation [1]. Typically, these data sets comprise one modality such as synthetic aperture radar (SAR) [2-4], wide-area motion imagery (WAMI) [5-8] or video [9-12]. Other data sets include two modalities such seismic-acoustic [13, 14] and audio-video for data fusion research [15, 16]. Recent results extend data sets for events and scenarios [17-20]. However, there is a need for multi-mode data set that incorporates attributes of the many potential sensors in a common scenario.

The Air Force Research Laboratory (AFRL), Information Directorate (RI)[1] conducted a multi-modal data collection, called: *Experiments, Scenarios, Concept of Operations, and Prototype Engineering* (ESCAPE). Figuratively ESCAPE describes a theme of the collection, as will be seen, of targets leaving the observed scene, then potentially re-emerging, and hence *escaping* detection and tracking. The challenge is to use multi-modal upstream data fusion approaches to determine unique joint multi-modal signatures that distinguish targets in stressing conditions such as interference, false targets and low received Signal to Noise (SNR) ratios.

The purpose of the ESCAPE multi-source data collection was to collect data on various ground target scenarios for use in advanced data-fusion research studies. Previous efforts [21-24], investigated pre-detection (upstream) level fusion of multi-modal signatures using simulated simultaneous Infrared (IR), Full Motion Video (FMV) and Passive Radio Frequency (P-RF) data collected from moving emitters. The ESCAPE test significantly enhances complexity (and opportunity) by increasing the number of modalities utilized as well as including outdoor experimental irregularities. The test utilized Commercial off the Shelf (COTS) sensor equipment providing simultaneous, heterogeneous collection with P-RF, radar, Electro-optical (EO), IR, seismic and acoustic sensing modes. Target types included ground-based vehicles such as a pickup truck, panel van, and utility vehicles.

The ESCAPE test commenced during the summer/fall of 2018 within the AFRL Stockbridge Test Site (STS) (Stockbridge, NY) in which all sensors would have simultaneous Line of Sight (LOS) viewpoints, noting that some sensors would experience blockages as targets move around obstacles, trees, and buildings.

The rest of the paper is as follows. Section 2 describes the location and scenario for the ESCAPE data set. Section 3 details the equipment used and the simultaneous data collection layout. Section 4 gives a few examples of the multi-modality data collected. Section 5 provides a summary and future research.

[1] RI – Research – Information Directorate
Approved for Public Release; Distribution Unlimited:
88ABW-2018-5339

978-1-5386-6854-2/19/$31.00 ©2019 IEEE

2. Collection Location and Scenarios

Location

The ESCAPE data collection was performed at the AFRL/RI Stockbridge Test Site (STS). The location is in a rural part of central New York (NY) state near Stockbridge NY, 43.031897° N, 75.651311° W. The STS is a 300 acre, partially wooded site, formally an AF Radio Frequency (RF) and antenna pattern measurement facility re-purposed for Small Unmanned Air Systems (SUAS), optical, expanded RF, cyber and Intelligence, Surveillance, and Reconnaissance (ISR) research. Figure 1 shows the overall site and location of the ESCAPE test.

Figure 1. Stockbridge Test Site (STS), Stockbridge, NY. Shaded region indicates location of the ESCAPE data collection. Northerly direction is at the top of the picture.

The location of the ESCAPE collection within the STS provides some unique features and provides simultaneous Line of Site (LOS) of the target scene from a majority of the sensors participating in the test; where the sensor layout is described in Section 3. The terrain features include flat grass fields, dirt roads, asphalt/concrete roads, sparse-tree hedgerows, and a large commercial steel building. The building, known as the *Butler Building*, provides a *tunnel* like feature allowing vehicles to enter/exit from the South and enter/exit from the North. The scene allows for performance evaluation of target representation approaches, fundamental for optimal fusion performance. For example, ground vehicle scenarios include a vehicle(s) that enters the building, and a vehicle(s) that leaves the building, begging the question - *is it the same vehicle*?

Targets

Ground targets used for the ESCAPE data collection, in the scenarios described below, are pictured in Figure 2. They consisted of utility vehicles (e.g. John Deer Gator), a pickup truck, panel van and a stake rack truck. One interesting variation in the target set was the use of one diesel and two gas Gators. All three Gators were 4-seat versions, hence having essentially the same length and width; however, the diesel gator had a different acoustical and presumably seismic signature due to the nature of the diesel engine vs. the gas engine. It is of interest to determine if algorithmic methods applied to the various modality signatures of these vehicles can disambiguate them sufficiently. In many of the use case scenarios, one version of the gator would enter the Butler building and another would exit; *can advanced upstream fusion of the multi-modality signatures make this differentiation?*

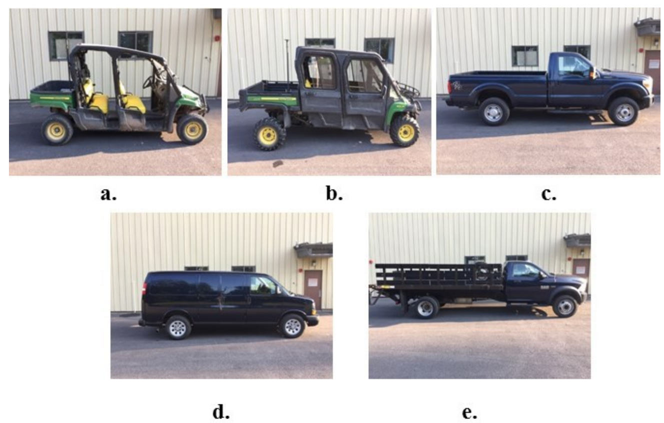


Figure 2. Ground vehicles used during ESCAPE data collection, a.) gas motor *Gator* utility vehicle, b.) diesel motor *Gator* utility vehicle, c.) pickup truck, d.) panel van, and e.) stake rack truck.

Scenarios

An objective of the ESCAPE collection was to record multi-modality data on diverse ground vehicle scenarios. Scenarios range from single vehicle trajectories to multi-vehicle behaviors. In any given scene, at least one vehicle was emitting, and in most multi-vehicle scenarios, two vehicles were emitting various communication waveform standards. The single vehicle scenarios allow researchers to focus on, and perfect, new algorithmic approaches for developing multi-modality target representations by exploiting the pre-detection level (*upstream)* sensor data available from the collection. Denser target scenarios (up to 4 vehicles) contain conditions of closely spaced targets, opposing targets, passing targets, move-stop-move trajectories, and LOS blockage. These scenarios should provide difficulties for traditional detection-level fusion approaches while potentially showing the benefit of pre-detection level approaches.

Figure 3 shows an example of a two-vehicle scenario conducted during the ESCAPE data collection. Colored red and yellow paths show the trajectories of two separate targets. Typically, the vehicles started and ended at the same time with speeds of 10-15 miles per hour (MPH). Variations to the scenario included different vehicle types and multiple vehicles. The sensor layout is also indicated Figure 3.

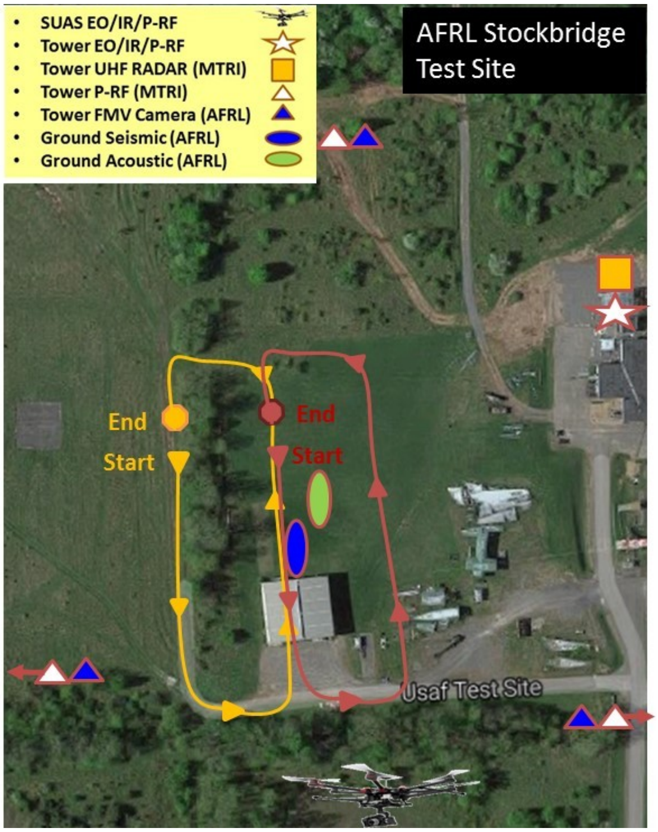


Figure 3. Ground vehicle scenario, two-vehicle case.

Figure 4 shows an extension to the scenario shown in Figure 3 by adding a third vehicle - the green path. This scenario is representative of the *ESCAPE* data collection title. Two vehicles enter the building as a third emerges. Question at hand, *is it one of the targets that entered the building or an entirely different target?*

Figure 5 depicts a multi-vehicle scenario, four vehicles in this example, which adds more diversity to the target scene. Two vehicles were emitting communication signals. The movement of all vehicles varied in terms of their motion. For example, the green path vehicle performed some move-stop-move variations while other targets passed each other. Other variations of this scene included vehicles overtaking the vehicle in front. These types of situations are expected to cause some issues with traditional post-detection level vehicle tracking approaches as well as the line of sight (LOS) blockage at some sensors produced from the westerly tree hedge row and the Butler Building.

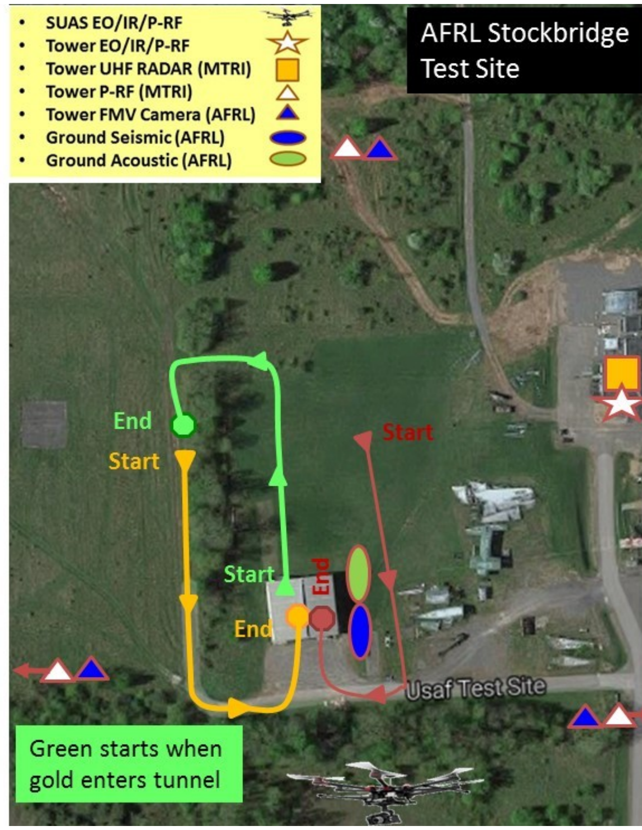


Figure 4. Ground vehicle scenario, Three-vehicle case.

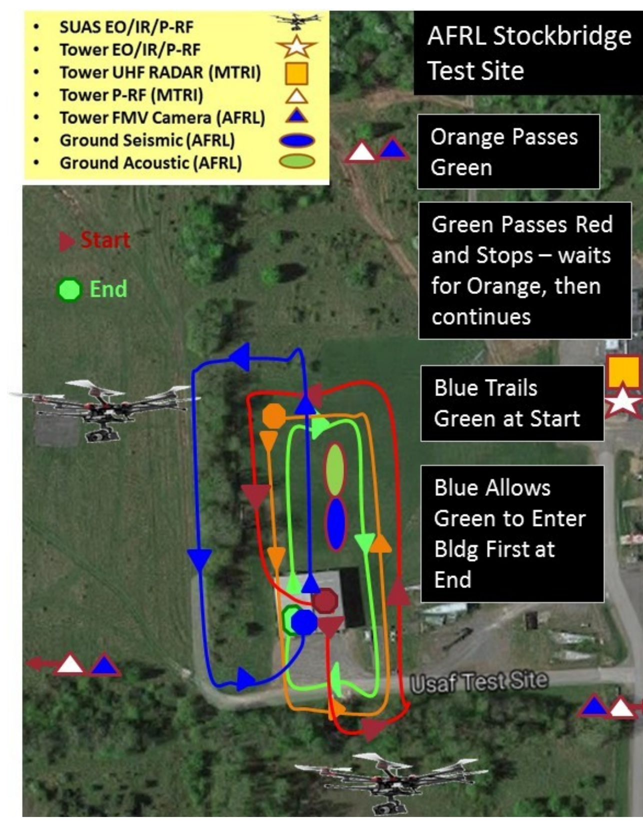


Figure 5. Ground vehicle scenario, four-vehicle case.

Emitters

To make the ground target signatures more discernable, one emitter was placed in two separate vehicles for all scenarios, with one emitter being used for the single target scenarios. Furthermore, the emitter signal's design simultaneously transmits 13 different transmissions separated in frequency. There were 11 typical communication modulation schemes that included Binary Phase Shift Keyed (BPSK), Quadrature PSK (QPSK), Offset QPSK (OQPSK), 8 PSK, 16 Quadrature Amplitude Modulation (16-QAM), 64-QAM, Gaussian Minimum shift Keying (GMSK), 4 Amplitude Shift Keying (4ASK), Frequency Modulation (FM), Amplitude Modulation Single Sideband Suppressed Carrier (AM-SSB-SC) and Amplitude Modulation Double Sideband Suppressed Carrier (AM-DSB-SC). Additionally two tones were added to make 13 total frequency channels.

Each emitter transmits the 13 frequency channels over a 4 MHz frequency band. One emitter would transmit over a 4 MHz band from 1240 MHz to 1244 MHz*;* referred to as *the low band emitter.* The second emitter, separated by 1 MHz from the first emitter, would transmit on a similar 4 MHz frequency band from 1245 MHz to 1249 MHz; referred to as *the high band emitter*. The total is 8 MHz worth of transmit signals, plus 1 MHz of guard band between them. It was designed to fit within the ESCAPE data collection receiver's bandwidth, particularly the ESCAPE payload (described in Section 3), of 12.5 MHz. Figure 6displays a spectrogram of the received data from one of the ESCAPE payloads when both emitters are transmitting. Note the 13 frequency channels in both the *low band* and the *high band*.

This design of the multiple transmit frequency channels allows the data user to select a waveform of choice through appropriate channel selection/filtering. Hence, only one collection scenario emulates a number of transmitter types for the desired research and data analysis interests, instead of collecting the given scenario 13 separate times.

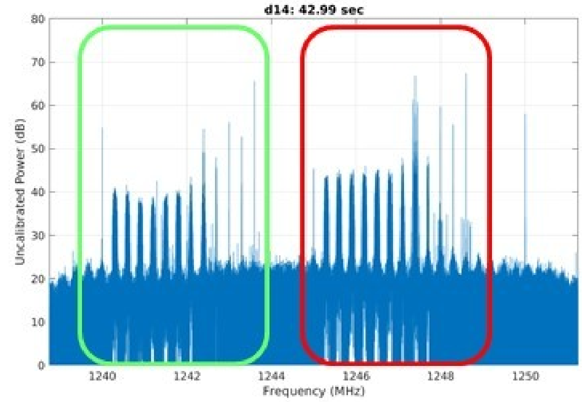


Figure 6. Emitter spectrum as seen by one of the ESCAPE payload RF receivers. 13 waveforms between 1240-1244 MHz and another copy of the 13 waveforms between 1245-1249 MHz.

3. Experiment Layout & Sensing Equipment

Experiment Layout

The orange shaded region in Figure 1 represents the area within the STS used for target activity during the ESCAPE data collection. Hence, sensors placed in proximity to this region for collection purposes. Figure 7 shows the specific layout of the sensing equipment used for the collection. There were 6 separate modalities, 8 sensor locations and over 20 total sensors utilized. The specific modalities include EO FMV, IR FMV, P-RF, radar, seismic and acoustic. The idea behind the sensor placement was to have a large geometrically diverse layout of the various modalities, with some co-location of some of the modalities. For example, one of the prime sensors was a collection of 3 modalities, co-located, including EO FMV, IR FMV, and P-RF (EO/IR/P-RF) - referred to as the *ESCAPE payload*, described below. Other co-located modalities included EO FMV and P-RF.

Sensors resided on towers, SUASs, ground tripods, and ground contact sensors. Figure 7 depicts the sensor layout at the STS and the associated towers and their heights.

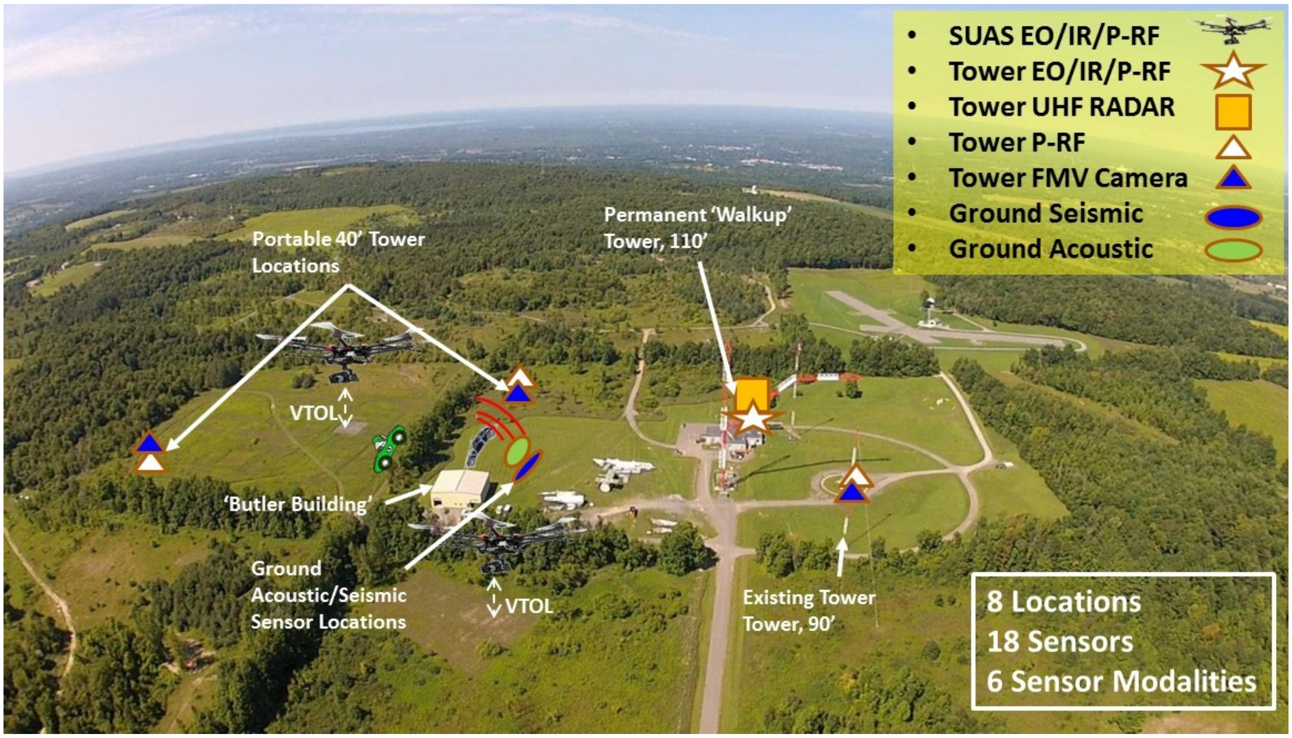


Figure 7. ESCAPE sensor modality layout at the Stockbridge Test Site.

Based on the sensor layout and the scenarios described in Section 2, a majority, but not all, of the sensors will view a given target simultaneously. The coordinated collection provides simultaneous multi-modality data on a given target.

ESCAPE EO/IR/P-RF Payload

The ESCAPE payload is a collection of three sensing modalities, EO FMV, IR FMV and passive RF (EO/IR/P-RF). The intent was to fly (hover) the ESCPAE payload on two separate SUASs (denoted SUAS EO/IR/P-RF in Figure 7), and have one tower mounted (denoted Tower EO/IR/P-RF in Figure 7). The payload is pictured in Figure 8Figure 8 in a configuration mounted under a DJI M600 SUAS Vertical Take Off and Landing (VTOL) aircraft.

The ESCAPE payload consists of the following equipment:

- Ettus B200 software defined radio (SDR) receiver
- LP0965 Log Periodic Antenna
- GPS
- FLIR Vue Pro-R Radiometric thermal camera
  - Radiometric: 640x512, 1 Frame Per Second (FPS)
  - Analog video: 320x240, 30 FPS
- Basler ace acA3800-14uc camera
  - 3840x2748, 14 FPS
- Intel NUC NUC6i5SYK Computer
- MaxAmps LiPo 2800 4S 14.8V Battery Pack (Qty: 2)

In order to accommodate mounting on an SUAS, the payload design approximated the size of 20cm × 16cm × 4cm, and with a mass of no more than 2500g (5.51 lbs). The components of the payload are self-contained and do not require power or control signals from the SUAS. All power consumed by the payload comes from its internal batteries. All three sensor payloads are operated remotely via standard wireless networking.

Figure 8. The ESCAPE payload, mounted to DJI M600 SUAS, featuring an EO FMV camera, an IR FMV camera and a SDR-based P-RF system with log periodic antenna.

Passive RF Receivers (P-RF)

Three P-RF receivers, independent of the ESCAPE payload, were placed on towers, indicated as Tower P-RF in Figure 7. These three sensor synchronously measure RF signals using an Ettus N210 software defined radio receiver. The nodes operated remotely via a standard wireless network. Data is recorded in real-time to the hard drive of the Macbook Pro with adequate recording capability for the intended collections. Specifics on each receiver node are:

- Ettus N210 software defined radio (SDR) receiver
- GPS
- Apple Macbook Pro computer
- External hard drive for additional data storage
- AH Systems SAS-510-4 Log Periodic (LP) Antenna

Each node was mounted to a 40' portable tower. The antenna was mounted directly below an EO camera discussed below. Figure 10 shows the mounting configuration.

UHF Radar

The UHF radar used in the ESCAPE collection was comprised of an Akela RF Vector Signal Generator, two Akela tapered horns (one transmit, one receive) and a control laptop. The hardware operates within a frequency range of 380 – 3000 MHz. For the ESCAPE collection the frequency was limited to 1700 - 2400 MHz (avoiding 1559 – 1610 MHz) with a transmit peak power of 100 milliWatts (mW). It is a software-designed system capable of a stepped frequency continuous wave mode operation. The equipment was mounted on the STS 110' tower, focused in the direction of the ESCAPE data collection, shown in Fig. 9.

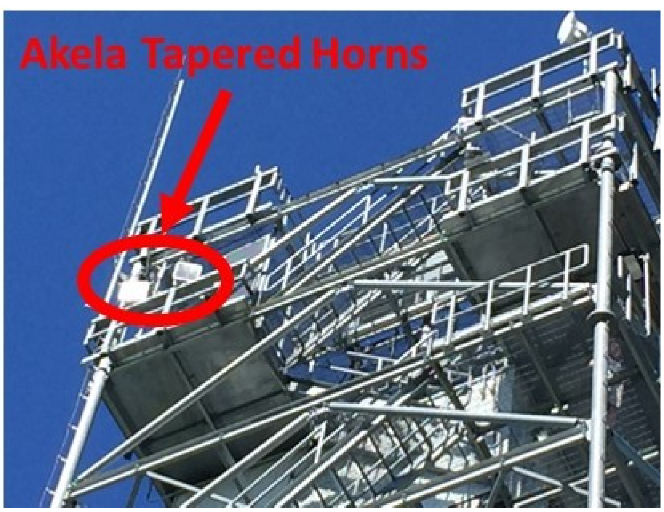


Figure 9. Akela tapered radar horns (1 transmit, 1 receive) mounted to the STS tower, 110' above ground (outlined in red).

Electro-Optical Cameras

Three EO FMV cameras (denoted as *Tower FMV Camera* in Figure 7) mounted atop 40' portable towers capture the orchestrated activity during the ESCAPE data collection.Each camera location contained the following:

- AVT Prosilica GX3300 GigE Camera (resolution: 3296x2472, 12 bit color)
- FLIR PTU-D48E Pan and Tilt Unit (PTU)
- Nvidia Jetson Tegra TK1 control board
- SATA hard drive
- Control laptop

Control of the camera was via a wireless network. The camera captured 7 frames per second (FPS). A weather tight enclosure protects the equipment. Figure 10 shows the deployment of the EO camera (in weather-tight enclosure), mounted above the P-RF log periodic antenna mentioned above.

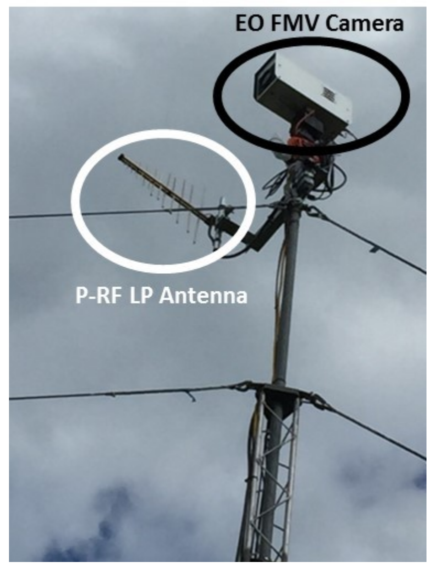


Figure 10. EO camera (in enclosure) mounted above the P-RF log periodic antenna atop a 40' portable tower.

Acoustic Sensor

The ESCAPE data collection is unique in that is employed non-traditional ISR sensors such as above-ground acoustic and seismic modalities. The acoustic sensor should be able to provide unique signatures of the different ground targets and allow for beamforming as it consists of two arrays that were approximately 2-3' off the ground. Each array has 8 elements and the arrays are placed orthogonal too each other. Figure 11 presents the acoustic sensor setup. The acoustical sensor consists of the following components:

- 16 Bruel & Kjaer 4952 outdoor microphones
- 2 Sound Devices 788T 8 channel recorders
- Pre-amplifiers
- 24 bit A/D

Figure 11. Acoustic array consisting of 16 mircophones.

Seismic Sensor

Seismic sensing adds an additional interesting component to the ESCAPE data collection as it is presumed that the different ground targets will have uniquely different seismic signature profiles. The seismometer is a COTS product referred to as a Raspberry Shake, shown in Figure 12. The Raspberry Shake is a Raspberry Pi 3 controlled single channel electronically extended 4.5 Hz geophone with a 24 bit digitizer sampled at 50 Hz with the data presented in miniSEED format. The Raspberry Shake is traditionally used for earthquake recordings up to 300 miles from the epicenter. For the ESCAPE data collection, 10 units were deployed around the testing area. Each sensor was placed in contact with the ground and located on a grass field, asphalt driveway, and the concrete floor of the Butler building.

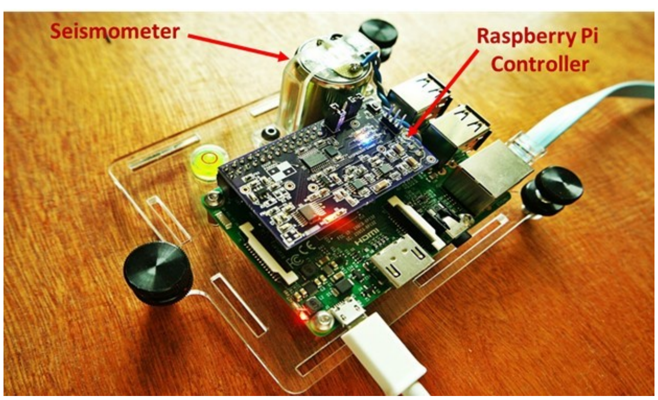


Figure 12. Raspberry Pi 3 based seismometer, *Raspberry Shake.*

4. Data Collected

With over 20 sensors collecting during any given ESCAPE scenario run, a number of combinations of sensing modalities exist for data-fusion potential. Nearly 60 ground-target scenarios exist, each being on the average of 1 minute in length. The total data size of all data is approximately 15 Tera Bytes (TB). Availability of portions of this data collection to the public will be forth coming and are in the review process at the time of writing this paper. Please contact Peter Zulch, AFRL, for availability and distribution.

A quick look at the data show relationships between the various modalities. Future joint use of the upstream multi-modal data is expected to produce more unique relationships and target representations such as manifold [26] and topological feature visualizations [27, 28]. In particular, advanced fusion algorithms, designed to ingest heterogeneous, upstream data afford associations between the various signatures in an autonomous fashion.

EO and IR Association

Figure 13 displays a snapshot in time from the recorded video data from 3 of the ESCAPE payloads, positioned as shown in Figure 7. In Figure 13, row (a) is from the 110' foot walk up tower, row (b) is from the most Westerly SUAS position, and row (c) is from the most Southerly SUAS position. Interestingly, some of the moving vehicles exist in most of the cameras simultaneously.

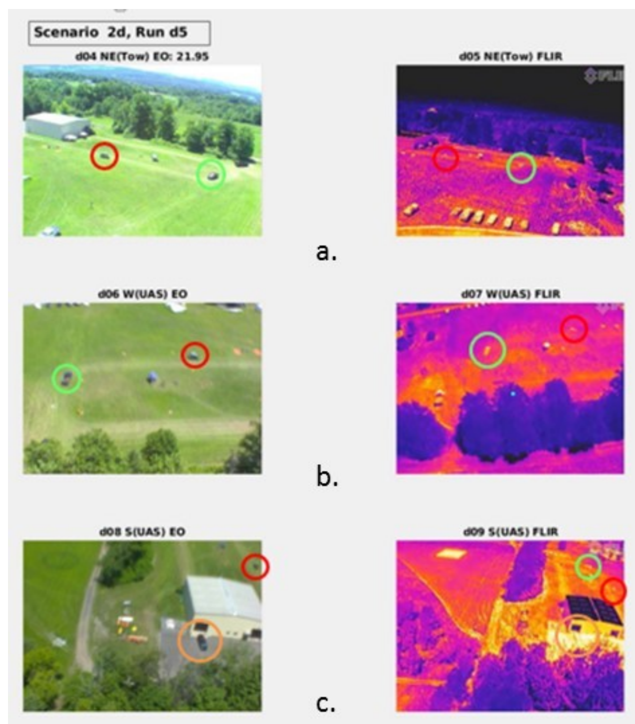
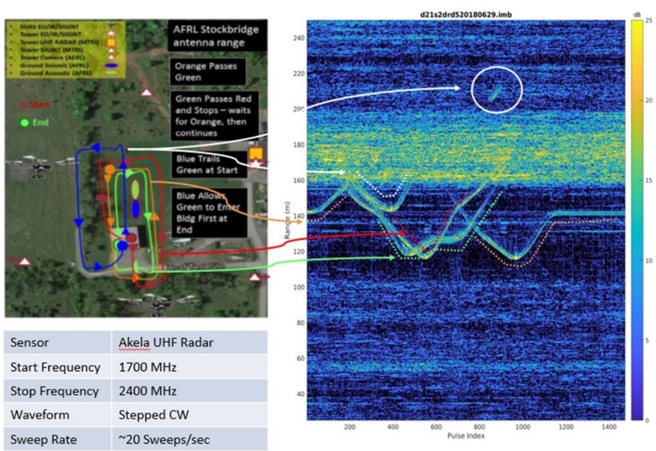


Figure 13.ESCAPE payload EO and IR frames during a data collection run of the scenario shown in Figure 5 (4 vehicles). a.) 110' tower view, b.) Westerly SUAS view, c.) Southerly SUAS view. Color code: red- Gator, green – pickup, orange – van.

The objective in fusion research will be to determine if a joint representation of each target can be produced that is unique to the given target in order to accurately and optimally improve target detection, improve discriminability, and improve target tracking. With overlapping fields of view across the three camera locations and across the EO and IR modalities, image fusion [29, 30] could yield robust results.

Radar Returns

Figure 14 displays the UHF radar returns for the multi-vehicle scenario depicted in Figure 5. The right side of the Fig. 14 displays amplitude (color code) vs range (vertical axis) vs time (horizontal axis). As indicated, certain paths, predictably, have different *traces*. For example, the orange path vehicle, panel van, starts in view of the radar and moves away from the radar until it is lost in the Butler building, as indicated in the radar return. The wide band of returns between 160 m and 200 m represents the Butler building and tree line scattering, and hence, the van return gets consumed by this clutter as it is blocked from the radar. Later in time, the van re-emerges from the Butler building and is easily detectable in the diagram between pulse indexes 800 and 1400.



Sensor	Akela UHF Radar
Start Frequency	1700 MHz
Stop Frequency	2400 MHz
Waveform	Stepped CW
Sweep Rate	~20 Sweeps/sec

Figure 14. UHF radar returns (right side) of the multi-vehicle scenario shown in Figure 5. Returns are in range (vertical axis) vs. time (horizontal axis). Colored arrows relate the vehicle paths with the radar returns.

The data provides an opportunity for more interesting fusion approaches make use of the radar phase-history information in order to assign each target a unique feature that correlates with other modality specific signatures.

5. SUMMARY

The field of heterogeneous data fusion is rapidly changing due to the accessibility of high quality multi-modal digital data. Access to raw unprocessed data from modern digital solid-state systems will greatly expand the potential to exploit multi-modal data. The ESCAPE data collection is an example of the kind of data that could be readily available by today's advanced technology of ISR sensors. Having a data set to explore new methods of processing such multi-modality, high dimensional and complex data should yield improved performance benefits.

The ESCAPE data collection collected heterogeneous multi-modal data of diverse target scenarios in order that researchers can explore the possibilities of utilizing such data. By jointly exploring data in its unprocessed form will greatly improve detection, recognition, classification, identification, and tracking performance for maneuvering targets in difficult sensing conditions. The challenging target behaviors and operational conditions, that degrade current post-detection fusion algorithms, include weak received signal-to-noise ratio (SNR) target signatures, false targets, dense target environments, complex target kinematics and difficult collection geometries.

The data set along with the baseline methods are available for further research and investigation; however, parts of the data set are sequestered for algorithmic testing. Future challenge problems, metrics, and variations will be compiled from the data set to motivate the community for advances in upstream data fusion (UDF) [31], classification [32], target tracking [33], and machine learning [34]. Examples include compression, user interpretability, and downstream data-fusion methods [35]. Likewise, continual use of the data includes adding to the knowledge of the data set to include software developments in signals processing, registration, and metrics for future comparisons and data analytics.

ACKNOWLEDGEMENTS

The authors thank the Air Force Research Laboratory, Information directorate, and the Air Force Office of Scientific Research for continuing to fund research that can utilize the collection data described in this paper. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of Air Force Research Laboratory, or the U.S. Government.

REFERENCES

[1] G. Seetharaman, A. Lakhotia, E. Blasch, "Unmanned Vehicles Come of Age: The DARPA Grand Challenge," *IEEE Computer Society Magazine*, Vol. 39, No. 12, pp. 26-29, Dec 2006.

[2] T. Ross, S. Worrell, V. Velten, J. Mossing, M. Bryant, "Standard SAR ATR Evaluation Experiments using the MSTAR Public Release Data Set," *Proc. SPIE*, Vol. 3370, 1998.

[3] A. K. Mishra, B. Mulgrew, "Multipolar SAR ATR: Experiments with the GTRI Dataset," *IEEE Radar Conf.*, 2008.

[4] S. M. Scarborough, C. H. Casteel Jr, L. Gorham, M. J. Minardi, U. K. Majumder, M. G. Judge, E. Zelnio, M. Bryant, "A Challenge Problem for SAR-based GMTI in Urban Environments," *Proc. SPIE*, Vol. 7337, 2009.

[5] O. Mendoza-Schrock, J. A. Patrick, E. Blasch, "Video Image Registration Evaluation for a Layered Sensing Environment," *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, 2009.

[6] K. Palaniappan, M. Poostchi, H. Aliakbarpour, R. Viguier, J. Fraser, F. Bunyak, A. Basharat, S. Suddarth, *et al*., "Moving Object Detection for Vehicle Tracking in Wide Area Motion Imagery Using 4D Filtering," *Int'l. Conf. on Pattern Recognition (ICPR),* 2016.

[7] K. Liu, S. Wei, Z. Chen, B. Jia, *et al*., "A Real-Time High Performance Computation Architecture for Multiple Moving Target Tracking based on Wide-Area Imagery via Cloud and Graphic Processing Units," *Sensors*, 17(2), 356; 2017.

[8] D. Wang, M. Yi, F. Yang, E. Blasch, C. Sheaff, G. Chen, and H. Ling, "Online Single Target Tracking in WAMI: Benchmark and Comparisons," *Multimedia Tools and Applications*, 77(9): 10939-90960, May 2018.

[9] S. Oh, A. Hoogs, A. Perera, N. Cuntoor, C.C. Chen, J.T. Lee, S. Mukherjee, J.K. Aggarwal, H. Lee, L. Davis, E. Swears, X. Wang, Q. Ji, K. Reddy, M. Shah, C. Vondrick, H. Pirsiavash, D. Ramanan, J. Yuen, A. Torralba, B. Song, A. Fong, A. Roy-Chowdhury, and M. Desai, "A Large-scale Benchmark Dataset for Event Recognition in Surveillance Video." Proceedings of *IEEE Computer Vision and Pattern Recognition* (CVPR), 2011.

[10] P. Liang, E. Blasch, H. Ling, "Encoding Color Information for Visual Tracking: Algorithms and Benchmark," *IEEE Trans. On Image Processing*, Vol. 24, No. 12, Dec. 5630-5644, 2015.

[11] A. Freeman, H. Zelnio, L. Cain, E. Watson, O. Mendoza-Schrock, "Minor Area Motion Imagery (MAMI) Dismount Tower Data Challenge Problems," IEEE National Aerospace and Electronics Conference (*NAECON*), Dayton OH, 2014.

[12] R. Ilin, S. Clouse, "Extraction and classification of moving targets in multi-sensory MAMI-1 data collection," *IEEE National Aerospace and Electronics Conference (NAECON),* pp 387-391, Dayton OH, 2015.

[13] M. F. Duarte and Y. H. Hu, "Vehicle Classification in distributed sensor networks," *J. Parallel Dist. Computation*, 64. No. 7, 2004.

[14] E. Blasch, J. Dezert, and P. Valin, "DSMT Applied to Seismic and Acoustic Sensor Fusion," *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, 2011.

[15] E. Blasch,"NAECON08 Grand Challenge Entry Using the Belief Filter in Audio-Video Track and ID Fusion," *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, 2009.

[16] S.T. Shivappa, M. M. Trivedi, B.D. Rao, "Audio-visual Information Fusion In Human Computer Interfaces and Intelligent Environments: A survey," *Proceedings of the IEEE*, 98 (10), 1692-1715, 2010.

[17] R. I. Hammoud, C. S. Sahin, E. P. Blasch, B. J. Rhodes, T. Wang, "Automatic Association of Chats and Video Tracks for Activity Learning and Recognition in Aerial Video Surveillance," *Sensors*, 14(10): 19843-19860, 2014.

[18] J. Moon, Y. Kwon, K. Kang, and J. Park, "ActionNet-VE Dataset: A Dataset for Describing Visual Events by Extending VIRAT Ground 2.0,"*International Conference on Signal Processing, Image Processing and Pattern Recognition*, 2015.

[19] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, *et al*., "The Cityscapes Dataset for Semantic Urban Scene Understanding," *CVPR*, 2016.

[20] S. Y. Nikouei, Y. Chen, A. Aved, E. Blasch, "Toward an Event-Oriented Indexable and Queryable Intelligent Surveillance System," IEEE COMSOC MMTC Communications – *Frontiers*, 13(4): 33-39, July 2018.

[21] R. Niu, E. Blasch, P. Zulch, M. Distasio, D. Shen, G. Chen, Z. Wang, and J. Lu, "Joint Sparsity Based Heterogeneous Data-Level Fusion for Multi-Target Discovery," *Proceedings of the 2018 IEEE Aerospace Conference,* Big Sky, MT, March 3-10, 2018.

[22] D. Shen, P. Zulch, E. Blasch, G. Chen, Z. Wang, J. Lu, R. Niu, "Manifold Learning Algorithms for Sensor Fusion of Image and Radio-Frequency Data," *Proceedings of the 2018 IEEE Aerospace Conference,* Big Sky, MT, March 3-10, 2018.

[23] D. Garagic, J. Peskoe, F. Liu, M. Claffey, P. Bendich, J. Hinman, N. Borggren, J. Harer, P. Zulch, B. Rhodes, "Upstream Fusion of Multiple Sensing Modalities Using Machine Learning and Topological analysis: An Initial Exploration," *Proceedings of the 2018 IEEE Aerospace Conference,* Big Sky, MT, March 3-10, 2018.

[24] M. Robinson, J. Henrich, C. Capraro, P. Zulch, "Dynamic Sensor Fusion Using Local Topology," *Proceedings of the 2018 IEEE Aerospace Conference,* Big Sky, MT, March 3-10, 2018.

[25] D. Shen, E. Blasch, P. Zulch, M. Distasio, R. Niu, J. Lu, Z. Wang, and G. Chen, "A Joint Manifold Leaning-Based Framework for Heterogeneous Upstream Data Fusion," *Journal of Algorithms and Computational Technology* (JACT), 12(4): 311-332, 2018.

[26] C. Hertzberg, R. Wagner, U. Frese, L. Schroder, "Integrating generic sensor fusion algorithms with sound state representations through encapsulation of manifolds," *Information Fusion*, 14(1): 57-77 2013.

[27] B. Rieck, H. Mara, H. Leitte, "Multivariate data Analysis Using Persistence-Based Filtering and Topological Signatures," *IEEE Tr. Visualization and Computer Graphics*, 18(12): 2382-2391, 2012.

[28] J. Tierny, G. Favelier, J. A. Levine, C. Gueunet, M. Michaux, "The Topology Toolkit," *IEEE Tr. Visualization and Computer Graphics*, 24(1): 832-841, 2018.

[29] Z. Liu, E. Blasch, V. John, "Statistical Comparison of Pixel-Level Fusion Algorithms" *Information Fusion*, 36, 251-260, 2017.

[30] Y. Zheng. E. Blasch, Z. Liu, *Multispectral Image Fusion and Colorization*, SPIE, 2018.

[31] A. J. Newman and G. E. Mitzel, "Upstream Data Fusion: History, Technical Overview, and Applications to Critical Challenges," Johns Hopkins APL Technical Digest, 31(3): 215-233, 2013.

[32] W. D Van Eeden, J.P. de Villiers, R.J. Berndt, *et al*., "Micro-Doppler radar classification of humans and animals in an operational environment," *Expert Systems With Applications*, Vol. 102, July 2018.

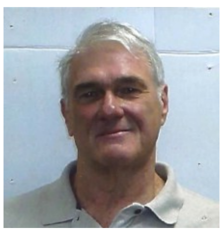
[33] L. Snidaro, J. Garcia Herrero, J. Llinas, E. Blasch (eds.), *Context-Enhanced Information Fusion*: *Boosting Real-World Performance with Domain Knowledge*, Springer, 2016.

[34] E. Blasch, S. Ravela, A. Aved (eds.), *Handbook of Dynamic Data Driven Applications Systems*, Springer, 2018.

[35] E. Blasch, H-M. Chen, J. M. Irvine, Z. Wang, G. Chen, James Nagy, Stephen Scott, "Prediction of compression induced image interpretability degradation," *Optical Engineering,* 57(4), 043108 2018.

BIOGRAPHIES

Peter Zulch *received his B.S., M.S., and PhD from Clarkson University in 1988, 1991, 1994 respectively. From 1994 to the present, he is a principle scientist at the Air Force Research Laboratory (AFRL). From 1994to 2007, he worked for the AFRL Sensors Directorate where his interests included multidimensional adaptive signal processing with applications to Airborne Early Warning RADAR, space based radar, waveform diversity, multi-static radar, and active noise control. From 2007to the present Dr. Zulch is employed by the AFRL Information Directorate applying the previous interests to signal intelligence pursuits such as geo-location and upstream data fusion. Dr. Zulch is a senior member of the IEEE.*



Marcello DiStasio *received his B.S. degree from SUNY Oswego in 1972 in Chemistry, and his PhD in Nuclear Physics from Michigan State in 1980. Following his PhD he was an American Physics Society post-doctoral fellow. He was employed at General electric, defense systems, Syracuse NY, from 1983-1990 as a research scientist. From 1990-2005 he was employed at Sensis Corp., Syracuse, NY, as a research scientist and director of advanced development. From 2005-2013 he was employed at Syracuse Research Corp. (SRC), Syracuse, NY as a senior research program manager. From 2013-2015 he was Chief Scientist for Ground Worx, Syracuse, NY. In 2015, Dr. DiStasio joined the Air Force Research Laboratory, working in the areas of signal analysis, data exploitation and machine learning.*

Todd Cushman *received his B.S. in Computer Engineering from Clarkson University in 2002 and M.S. in Software Development and Management from Rochester Institute of Technology in 2012. From 2002-2011 he was employed with the Air Force Research laboratory, Sensor Directorate, Rome, NY. His interests then included knowledge-aided signal processing and multivariate statistical analysis. Since 2011, Mr. Cushman has been employed with the Air Force Research Laboratory, Information directorate, Rome, NY. His areas of research include maleware analysis, automated cyber defense and biometric based user authentication.*

Brian Wilson *received his B.S.E. and M.S.E. in Electrical Engineering, and a M.S. in Biomedical Engineering from the University of Michigan, Ann Arbor. Since 2006, he has been a Research Engineer at Michigan Tech Research Institute (MTRI), a nonprofit institute of Michigan Technological University. He is exploring topics such as multi-sensor fusion, passive RF imaging, automotive active safety systems, through-wall RF imaging, signal and image processing, and automated remote sensing applications. He also is involved in RF measurement planning and data collection, having participated in over 20 measurement campaigns. He has worked on projects such as wind turbine clutter mitigation, passive interferometric imaging, target RCS recognition, and coherent radar/RF/video simulation. Mr. Wilson is a member of the IEEE.*

Ben Hart *received his B.S.E. in Electrical Engineering and M.B.A. from Michigan Technological University in 2008 and 2014 respectively. Since 2008 he has been employed as Research Engineer at Michigan Tech Research Institute (MTRI), a nonprofit institute of Michigan Technological University. His work interests include computer system networking, hardware prototype development and sensor signal processing. He also is involved in measurement planning and data collection for RF, EO, and radar systems, having participated in over 20 measurement campaigns. .*

Erik Blasch *received his B.S. in Mechanical Engineering from the Massachusetts Institute of Technology (1992) and PhD in Electrical Engineering from Wright State University (1999) in addition to numerous Master's Degrees in Mechanical Eng., Industrial Eng., Electrical Eng., medicine, military studies, economics, and business. He has been with the Air Force Research Laboratory since 1996 compiling over 700 papers. He is a Fellow of IEEE, Fellow of SPIE, and Associate Fellow of AIAA. His areas of research include target tracking, image fusion, information-fusion performance evaluation, and human-machine integration.*