

Human Event Camera Teaming

Erik Blasch^{1*}, Hadi Ali Akbarpour², Austin Downey³

¹ MOVEJ Analytics, Fairborn, OH 45324

² Saint Louis University, Saint Louis, MO 63103

³ University of South Carolina, Columbia, SC, 29208

ABSTRACT

Event Cameras (ECs), or Dynamic Vision Technologies (DVT), have been developed for capturing motion of objects, reducing bandwidth from sending image frames, and increasing responsiveness for change detection. While many EC cameras are on the market, there are many performance issues to consider beyond the hardware performance such as the interaction with users for domain applications. In this paper, we explore ideas of ECs to potentially enhance human machine teaming for object detection and recognition tasks. The examples presented demonstrate the possible impact of ECs on a human cognitive work assessment for information fusion applications of space object awareness, high-rate structural health monitoring, and safety vigilance. The ideas presented motivate future test experiments with ECs to enhance human-machine teaming for surveillance, maintenance, and detection.

Keywords: Data Fusion Information Group Model, Information Fusion, User Refinement, Deep Learning, Digital Twins, Event Cameras, Human-Machine Teaming

1. INTRODUCTION

Data and image fusion methods can be computationally expensive, incur time delays, and require modifications to meet bandwidth requirements [1,2]. For example, when sensors operate at the edge, there is a need for efficient and scalable methods [3]. For a decade, researchers were interested in new technology, but the user perception and interaction also has to be considered [4,5] for meaningful use of the technology. Recently, event cameras or dynamic vision technologies are being developed that can support human-machine teaming (HMT) through direct application or with digital twin technology [6]. This paper presents a discussion to set the stage for human-EC teaming (HECT) experiments. Figure 1 presents as general concept to deploy event cameras for human cognitive situation awareness.

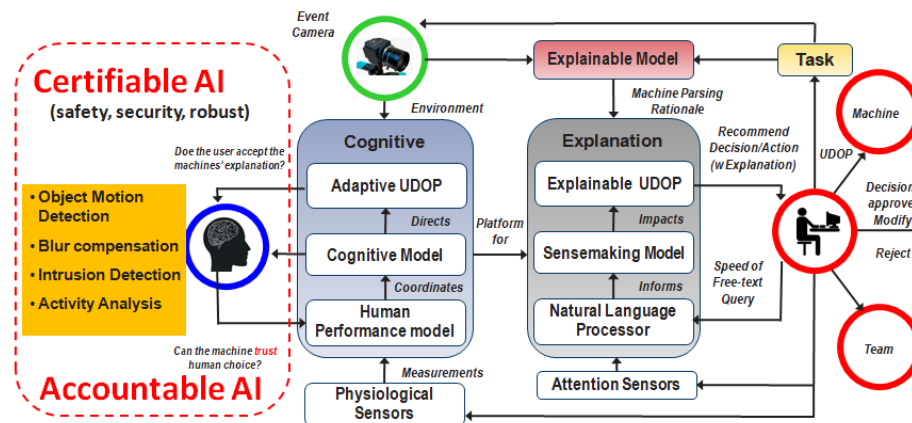


Figure 1 – Human Machine Teaming with Event Cameras.

Event cameras have been on the market for many years and include a few manufactures for imaging systems, especially visual tasks. Applications include manufacturing, inspection, object tracking, object recognition, and target tracking. Inherent in these designs are quick readout of change detection (CD) of pixel intensities. For a stable camera tracking a

*erik.blasch@gmail.com

moving object, the pixels that change in intensity indicate the movement of an object. By only outputting the pixels that change intensity, a form of data reduction results to save bandwidth. Among these advancements, there has yet to be studies and HECT experiments of the EC system, to include the sensor chosen, exploitation method, domain application, as well as the human operator.

Among the opportunities of such EC deployment, few HMT assessments have been performed as compared to traditional camera methods [7]. As with other video systems, images or exploited images are presented to the user to determine their performance analysis. Such constructs as valiance, change blindness, and perception resulted in initial studies in the 1970s. With the advent of exploitation computer vision methods, many HMT assessments included Automatic Target Recognition (ATR) methods (1980s) [8]. In the 1990s, machine learning transformed the video presentation to include that of the ATR that inherently would enhance the operator performance to the extent humans relied on the results [9]. In the 2000s, the development of imaging systems included image quality estimation [10], required registration [11], provided wide-area coverage [12], and conducted performance assessments such as with electro-optical/infrared systems [13]. Key to these developments was information maneuverability for decision making [14,15]; getting the results in a timely manner. Furthermore, in the last decade, deep learning has transformed image processing. Most recently, with the surge of large language models (LLMs), many research studies with operators have utilized visual language models (VLM) [16]. Using the trends from other technology, then there is a need for robust studies to assess event cameras beyond just the hardware and software exploitation methods, but also that of the human-EC teaming (HECT).

Event analysis is an important concept rooted in computer vision, psychology, and language. Specifically, the semantic challenge is between “event” and “activity”, as shown in Figure 2. Based on prior work, [17], it is assumed that an *event* is a specific instant in time, whereas an *activity* has duration [18]. An event could be change detection. Atomic events can then be aggregated to determine behavioral activity. Furthermore activities can lead to entities of behavior that can be semantically labeled. Currently, LLMs [19,20] can be used to query sensing knowledge and label activities, behaviors, and results; while also providing a narrative, such as human activity recognition behavior [21,22,23,24,25]. Examples of imagery-detected events can be combined with chat [26], text [27], cyber [28], cyber-physical systems [29], etc. for situation activity awareness. The event change can inform anomaly detection in the domains of cyber, energy, and surveillance [30].

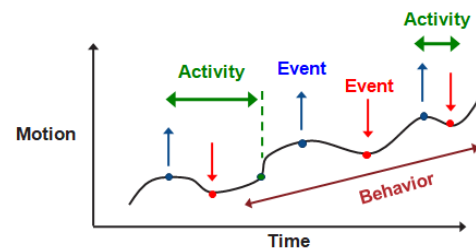


Figure 2 – Event versus Activity

In addition to video ECs, devices are being developed for event-based analysis over sensors such as infrared (IR) [31,32,33], radar [34], hyperspectral [35], acoustic [36], or combinations such as Electro-optical/IR [37] and other sensors that focus on the “event” or change in the sensing field. In the coming years, there should be a variety of systems available that can transform various surveillance tasks that use edge devices such as internet of things (IoT) sensors [38]. For example, a current EO/IR system [39,40] could be replaced with an EO/IR EC for safety, privacy [41], and security [42] analysis in edge-based [43], fog-based [44], or cloud-based [45] systems. Multimodal ECs could enhance complex system analysis [46]. Furthermore, with physics-based simulation, realtime data collection would facilitate scene recognition [47] and target tracking [48,49], or combinations [50]. A good example of object tracking is using an EC to enhance distinguishing between movements of animals and humans [51], that is useful for autonomous cars [52].

Among the progress in computer vision, traditional frame-based cameras have challenges like limited temporal resolution, restricted dynamic range, motion blur, and which limit their use in various scenarios. Recent developments include neuromorphic dynamic vision sensors (DVSs) that are inspired by biological vision systems such as spiking neural networks [53]. DVSs offer pixel-level detection of light intensity changes and a profound shift with exceptional temporal resolution by generating a continuous stream of events that encode polarity, location, and time. DVSs have shown remarkable improvements over traditional cameras with a dynamic range of 140 dB (compared to 60 dB), minimal latency, resilience to uneven lighting, low power consumption of just 1mW, and ultra-high temporal resolution over 100,000 frames per second [54]. DVSs are a transformative advancement in sensing technology to improve autonomous systems, navigation, object detection, space situational awareness, depth estimation, gesture recognition, and structural health monitoring. In addition, recent advancements of DVSs calibration, frame reconstruction, super-resolution, rolling shutter correction, and data compression, should improve these applications. Additional, when utilized

as a data-driven approach combined with physics-based simulation in the Dynamic Data Driven Applications Systems (DDDAS) framework [55,56], DVSs can be used in dynamic digital twin construct.

While the concepts presented in the paper are exploratory, the motivation is to start the HECT discussion. The rest of the paper is as follows. Section II overviews the event camera concept. Section III highlights directions with human imaging performance assessment. Section IV showcases current examples. Section V provides a discussion and Section VI conclusions and a way forward.

2. EVENT CAMERAS

Neuromorphic dynamic vision sensors (DVSs), or ECs, offer a paradigm shift from traditional frame-based snapshot imaging to dynamic, event-based capture; that is transforming visual sensing. Inspired by the human visual system, these DVSs sensors detect changes in light intensity at each pixel asynchronously, independently, and dynamically, that provide a realtime response. With the light intensity change detection operation, DVSs have these advantages [57]:

- *Superior Dynamic Range*: With a dynamic range of 140dB—vastly surpassing the 60dB offered by conventional cameras—DVSs can handle a wide range of illumination levels, from the brightest sunlight to dim moonlit scenes.
- *Low Power Consumption*: Operating on just microwatts of power (10 mW vs 1.5 W of standard cameras), DVSs are highly suitable for energy-constrained applications.
- *Ultra-High Temporal Resolution and Low Latency*: DVSs achieve an exceptional time-resolution equivalent of over 10,000 frames per second due to their microsecond-scale latency, enabling the capture of extremely rapid movements, such as a projectile in flight.
- *Enhanced Low-Light Performance*: Capable of operating in lighting conditions as low as 0.08 lux, which is about the illumination of a full moon on a clear night, DVSs are exceptionally sensitive in near-darkness.

By monitoring each pixel independently for the light intensity brightness, DVSs provide the principle of *change detection* (CD). When the brightness change exceeds a threshold, the pixel generates an event containing the pixel coordinates (x, y) , timestamp (t) , and the change's polarity p (increase or decrease). The independent and asynchronous stream of events (x, y, t, p) are used for further processing. Theoretically, the DVS is generally described by a simple model. Let $I(x, y, t)$ represent the light intensity at time t for pixel (x, y) . An event is triggered when the absolute change in intensity exceeds a threshold C :

$$|I(x, y, t + \Delta t) - I(x, y, t)| > C \quad (1)$$

where Δt is the time elapsed since the last event at that pixel (see Figure 3). The event polarity $p(x, y, t)$, is determined by the sign of the change:

$$p(x, y, t) = \text{sign}(I(x, y, t + \Delta t) - I(x, y, t)) \quad (2)$$

This simple event vision model highlights the inherent ability to detect and represent temporal information in a highly efficient manner. A sequence of events, denoted as E , takes the form $E = \{e_1, e_2, \dots, e_j\}$, for $j = 1, \dots, J$ and each event $e_j = \{x_j, y_j, p_j, t_j\}$ represents a tuple with image coordinates (x_j, y_j) , polarity p_j in the set $\{-1, 1\}$ and sometimes presented as $\{0, 1\}$, and timestamp t_j .

DVSs use the *Address-Event-Representation* (AER) format, originally proposed by Sivilotti [58], to mimic neural information transmission in biological systems [59]. AER is an event-driven, asynchronous protocol that transmits data only when pixels detect changes in intensity, reducing unnecessary bandwidth use, and increasing temporal sensitivity. However, it is noted that the electronic saturation can delay event output timing [60]. DVSs handle readout rates from 2MHz to 1200MHz, depending on chip and hardware capabilities [60]. Different event data representations have been developed for various tasks [61].

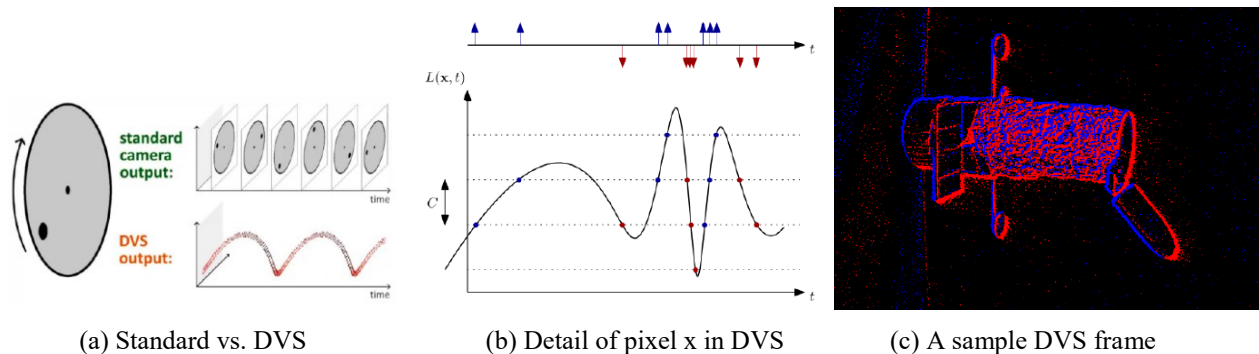


Figure 3 - Operating principles of DVS. (a) DVS observing a rotating disk with a black circle with contrast outputs from a standard camera. The standard camera captures images at regular intervals, often including redundant data without motion. In contrast, DVSs, as data-driven sensors, detect brightness changes with microsecond accuracy. (b) For pixel x , when the brightness shift exceeds the contrast threshold, C , a blue dot (positive event) or red dot (negative event) appears highlighting increased event rates during rapid signal changes. (c) DVS captured series of events in the satellite pose estimation dataset in [62]. Images (a) and (b) are from [63].

3. EVENT CAMERAS FOR HUMAN TEAMING

Processing data for “event” analysis can be fused with other contextual data to determine the situation, scenario, and timeline [64,65,66,67]. Here, an event is at an instance, while an activity has duration. Notionally, a behavior activity analysis can afford an element of situation assessment leading to human situation awareness [68,69]. A traditional example is the change in pose [70,71] either from a single camera or combined cameras [72] for object motion detection [73]. As illustrated in Figure 4 (a), the goal is to take the event signal (pixel, image, text) and determine the change. For the EC, the event change is the pixel; however, for a human the event might also have a semantic meaning. Using such concepts as DDDAS [74], the events can be listed in a dynamic database [75]. While EC EO imagery is well known, an example is for synthetic aperture radar (SAR) in which the visual inspection of the SAR imagery is difficult for a human to recognize. Hence, the pixel changes help identify the moving targets (although with low precision as compared to an EO/IR system). When the pixel change of man-made object is detected, the change detection can determine if the moving system is arriving or leaving a specific location to report object level change detection (OLCD) and/or the pattern of life [76].

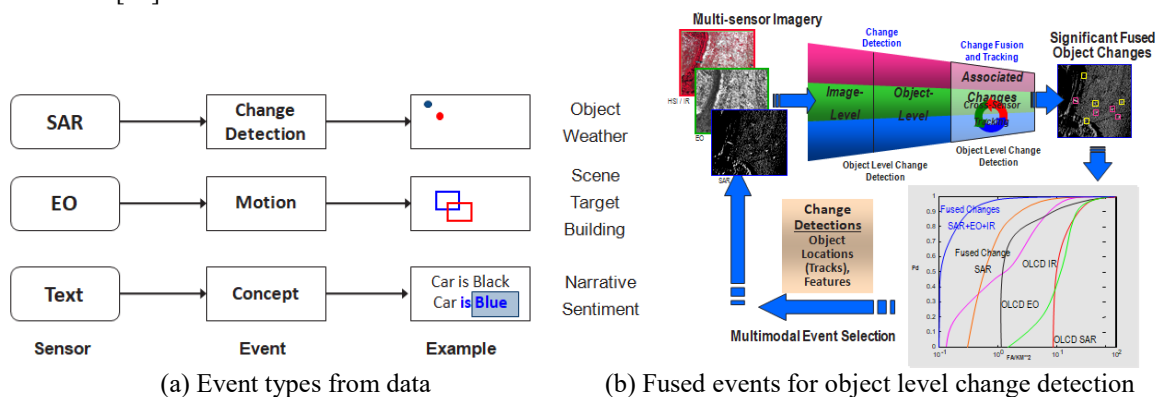


Figure 4 – Elements of sensor to event directions.

Human text also has changes. Entity semantic labels and concept drift are examples of text changes in classifying objects. For the SAR case, the changing perspective can have a change in the label; or for more informative changes is the analysis of the event-to-activity behavior. If an object is moving, it can cross a location demarcation such as a trip line in which the object moves across a geo-fence. Hence, in such a surveillance example, the moving from the CD can be observed and labeled. The label includes the temporal time (t) and duration ($t - t_i$), spatial location (x, y), and the semantic label of object type (o) and activity (a). These parameters can be used to build a narrative of a situation.

Using the concepts for situation analysis, ECs are assisting in a variety of applications such as ground target tracking to space object detection, structural health monitoring (materials awareness), and multimodal surveillance for day/night operations. Important is to note that the situation analysis includes the machine for situation assessment, the human for situation awareness, and correspondence with historical and cultural norms for situation understanding. Hence, the future of ECs can enhance applications from science experiments, autonomous processing, and forensics analysis. For example, a combination of capabilities can support autonomous scientific forensics imaging a damaged UAV. The EC can detect the UAV versus a bird and whether there is a bird strike collision. The UAV could have a broken part from which SHM is needed to inspect whether the damage is causing a variation in the flight profile. Furthermore, with DDDAS, a dynamic digital twin model can be used to do SHM to determine the severity of the damage that might cause safety and security concerns if the UAV flies into the wrong area. In addition to UAV SHM, the event processing can be extended to Lidar such as for environmental integrity (e.g., road embankments [77]).

Other examples include using the EC for direct detection of the inverse problem to estimate the scene. Using generative models is another case where ECs are showing promise in modeling. One can use the change detection from previous results to hypothesize the parameter change, Hence, a variation in the vibration (SHM), glint (object recognition), and flight trajectory can lead to UAV control [78]. Likewise, ECs can use diffusion models for change detection such as DaLE (Denoising diffusion probabilistic model – DDPM). Clearly, the belief in the results can aid in the assessment based on the event detection, object pose, situation plausibility, uncertainty quality, and data consistency.

ECs can enhance visual inspection, dynamic analysis, and trend monitoring in *maintenance*. DDDAS realtime dynamic approaches with DTs identify safety risks from damaged parts and needed repairs while increasing the remaining useful life (RUL) [79]. The EC results can be combined with dynamic digital twins using formal methods to enhance user responses [80] and safety-critical performance bounds [81] for operational effectiveness and decision support [82].

4. EXAMPLES

Among the many examples being explored, event cameras are widely used for space situational awareness (SSA), manufacturing, and surveillance. Many papers and publications highlighted the potential for ECs/DVSs and various groups have acquired event cameras for their areas of interest. This section will highlight examples collected for HMT use cases. Even with these use cases and the literature, little has been discussed on how the ECs will be utilized by operators. In some cases, the data would be aligned with EO imagery (e.g., video) with an overlay and in other cases, it would be the sole interface. Hence, the question is what is the EC impact on user perceptions, tasks, and workload?

A. Space Object Awareness

One of the promising approaches is event cameras which can capture dynamic motion without capturing the entire image (Figures 5 and 6) for SSA. A recent example is to use *event cameras* (EC) [83] to detect the motion change that can then cue electro-optical (EO) [84] and radio frequency (RF) observations. Event cameras have shown promise for sensing applications for target detection [85] and motion capture across many domains. An example of Satellite Pose Estimation and 3D Reconstruction [86] that was developed for DDDAS space applications is shown in Figure 5.

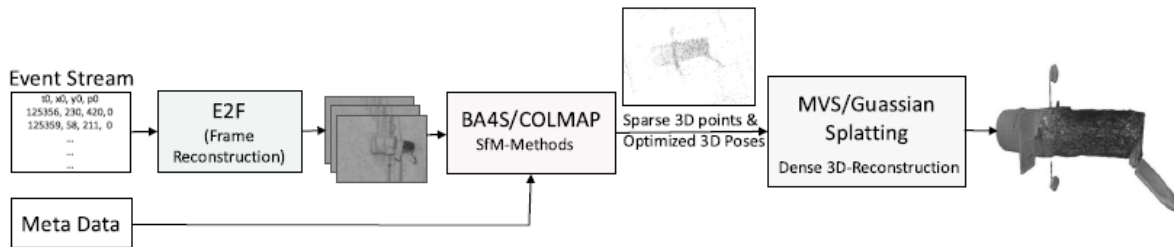
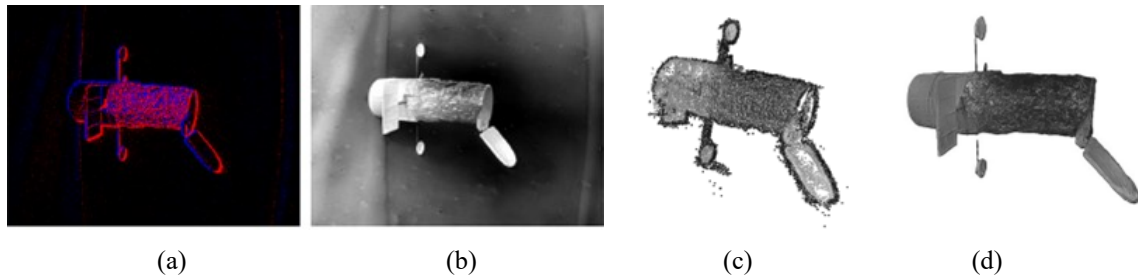


Figure 5 – The Event-based satellite pose estimation and 3D reconstruction pipeline.

Event streams are inputted into the event-to-frame (E2F) models, which output reconstructed frames. Subsequently, simulation methods such as Bundle Adjustment for sequential imagery (BA4S) [87] and Multi-View Stereo (MVS) use the frames to generate camera poses and sparse point clouds. Finally, the sparse point cloud from BA4S, along with the frames, are used as inputs for Gaussian Splatting (GS) techniques to obtain a dense 3D point cloud, which is subsequently utilized to create the final 3D satellite model (Figure 6). With EC results, satellite behavioral analysis can be enhanced [88] for orbital control [89].



(a) EC Frame, (b) Reconstructed Frame, (c) 3D Model Generated by MVS, (d) 3D Model Generated by GS.

Figure 6 – Event-based results for satellite modeling: (a) Positive (red) and negative (blue) events camera results over time. (b) Raw events satellite frame reconstruction. (c) BA4S with MVS generation. (d) BA4S with Gaussian Splatting dense 3D satellite model construction.

B. Structural Health Monitoring

While ECs for structural health monitoring (SHM) can enhance inspection, manufacturing, and observation, the concept has yet to widely discussed, such as incorporation with digital twins [90]. Current trends in digital twin developments

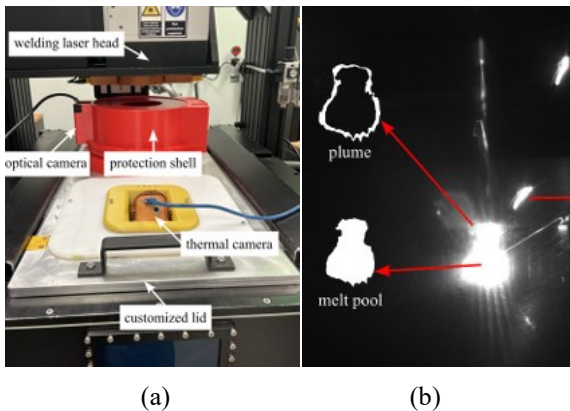


Figure 7 – Planned effort with EC for printed image melt manufacturing. (a) an event data collection setup with the optical and thermal cameras, and (b) extracted melt pool, plume, and spatter from the printing image.

seek high-rate updates [91,92,93]. Contemporary SHM focuses on options for normal computer vision tasks that would need to detect motions, however, not all motions are realized from RGB cameras alone. Figure 7 shows a case for melt manufacturing [94]. A melt pool in additive manufacturing is the localized volume of molten metal created by a high-energy heat source, such as a laser or electron beam, as it fuses powdered metal together. With the heat generated in the melt process, the RGB has a bright blur, while standard IR techniques could only reveal the external change of the melt. Hence, the EC has the potential to monitor the change in the heat and reveal a more precise boundary of the melt change. With the results, the manufacturing process could be further controlled to provide the right heat as the melt was developing and send the results for operator monitoring.

Three areas of possible EC use related to SHM are pipeline analysis, power grid inspection and wild fire analysis. With the example for the melt process, the ECs can enhance the combination of EO and IR analysis and methods of image translation [95]. Pipeline inspection includes assessment of corrosion, leaks, and sparks [96]. EO/IR systems have been developed for event analysis from which ECs could provide faster and more accurate analysis to provide mitigation response. The EC results can be combined with deep learning and digital twin analysis for detecting sparks that assist in power grid analysis [97,98] and a controlled physical response [99,100]. In a similar analysis, the detection of heat boundaries is similar to wildfire monitoring [101] and damage assessment [102]. Thus, there are many emerging infrastructure surveillance applications that can be transformed with event cameras.

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C. Safety Vigilance

The common example for event camera videos is surveillance; however, there is a need to investigate how a human would perceive the new EC information. Three examples are presented of change blindness mitigation, saliency affordance, and tangential motion perception. For purposes of HECT development, the goal is to design an emulation scenario for a on-orbit satellite servicing, assembly, and manufacturing (OSAM) where the robot user has to detect motion not seen by the manipulator [103], while utilizing the machine object awareness (Sect. 4A) and SHM (Sect. 4B).

C.1 Change Blindness

For the first case, it is to limit the effects of *change blindness*. Change blindness occurs when the human is staring at a video and focusing on the foreground for the object of interest while missing the background motion changes. Figure 8 showcases such experiments.

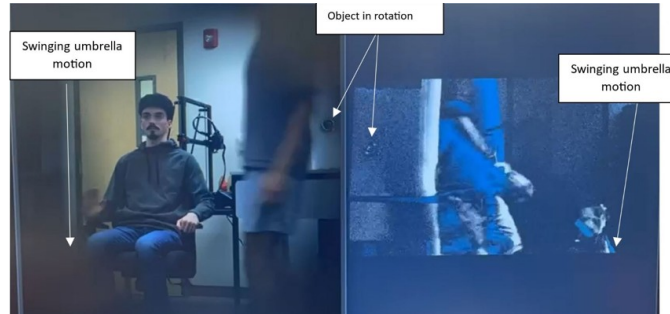


Figure 8 – Example where EC reduces change blindness

As shown in Figure 8, the person is sitting and another person walks by. In this case, the other person is carrying and swinging an umbrella as a spinning object, and there are occlusions. In a notional sense, the umbrella could be of concern at airport screening. The scenario video is presented to three groups – those with the video camera, those with the EC, and those with both. The metric evaluation would highlight whether key attributes were recognized in the video - such as what is the person sitting doing and what was the moving person holding? In this simple case, those users with both the video and EC detected the swinging object, while many with the video missed it as change blindness.

Another aspect from the video is limb movement and background interaction. The EC would detect simultaneous motion and there is a need to distinguish normal actions from that of behaviors that are abnormal. In the RGB, the event is barely noticeable as the user is focused on the moving person, but is revealed in the EC data.

C.2. Saliency Affordance

One of the key attributes of ecological psychology is affordances. An *affordance* is what the environment provides to the self-perception such as safe navigation and target recognition. For various human-machine teaming interfaces, the goal is to develop exploitation methods to assist human decision making. Since the EC compresses the motion data, it is helpful to determine the EC affordance of the amount, density, and coordination of moving objects. In this scenario, the three groups are given the video of moving traffic and asked human activity recognition (HAR) safety questions - what was the density of objects and how many objects? Hence, Figure 9 shows how the video could be used to afford the detection of the number of people when there are occlusions. Since there only two people and two objects, most subjects detected the people, but the swinging objects and count were missed with only the video data.



Figure 9 – Example where EC has affords saliency information

C.3 Tangential Motion Perception

For the third case, we are interested in sub-motions (Figure 10), such as limb movements compared to the torso walking movement. The videos collected have multiple people moving their limbs and the questions include – where was the human (robot moving to), what was the limb doing, and what was the limb holding? This example is a surrogate for OSAM robotics with platform movement and the manipulator motion. Such a scenario is evident in manufacturing, mobile robotic deployment, and inspection.

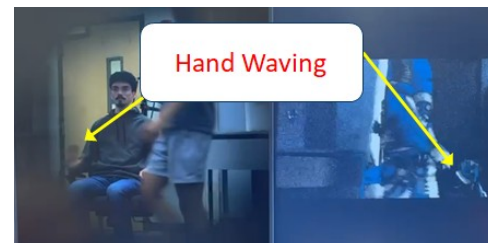


Figure 10 – Example where EC enhances tangential motion analysis

5. DISCUSSION

Many videos have been collected for HECT exploitation, so next stage is HMT understanding. Current results use the Situation Awareness Global Assessment Technique (SAGAT) with stopping the video and asking users' questions. Hence, the results reflect whether the user scored the correct answer. Since these are simple trials and results were successful, it demonstrates the validity of the EC to enhance operator performance. One direction is to expand on the HECT to further clarify user needs, display techniques, and complicated scenarios.

Future opportunities for ECs include multimodal sensing coupled LLMs for evaluation of local/global event analysis (to build activity narratives). A standard data set and benchmarking of HECT efforts is needed to establish compliance with current systems. For compliance, metrics need to be developed for measures of performance (accuracy, timelines, confidence) as well as measures for effectiveness of cost, throughput (to include compression), usability, and security. The Multi-Source AI Scorecard Table (MAST) criteria [104,105] would be helpful to determine the possible EC learning exploitation techniques which includes data source assessment (e.g., potential for detecting false data injection [106]), human-on-the loop analysis of alternatives (e.g.,[107]), and support for reporting (e.g., control actions [108]).

As this is first look at ECs for HMT, there are host of other event sensor emerging that could come in the next decade, so some additional insights into the sensor processing to assess blur, brightness, and saturation from which EC would help human operators. Combined with multisensor exploitation, information fusion, and deep learning assessment, many capabilities would result that can be tested. Finally, for HECT, a human workflow (e.g., alerts and exploitation), would need to be assessed for HMT situation assessment, training, and user refinement [109]. Future efforts would focus on HMT agentic multimodal event sensing using deep, reinforcement, active, and machine learning in DDDAS dynamical digital twins [110].

6. CONCLUSIONS

This paper sought to present ideas for human-machine teaming for event cameras. The paper overviewed how event camera data captures motion to enhance surveillance, monitoring, and situation assessment. The events provide instances that support demarcations of activities from which the activities lead to labeled behaviors. Three emerging examples were presented for space object assessment, structural health monitoring, and safety vigilance, showing motion detection to assist operators. These motivating examples demonstrate the capability of ECs for simple tasks and more complicated scenarios are needed for a thorough performance analysis with human subject tests to explore different concepts such as the inclusion of deep learning methods, digital twin models, and multimodal sensing.

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REFERENCES

- [1] Blasch, E., Llinas, J., Lambert, D., et al., "High level information fusion developments, issues, and grand challenges: Fusion 2010 panel discussion," *Int'l Conf. on Information Fusion*, (2010).
- [2] Blasch, E., Bosse, E., Lambert, D. A., [*High-Level Information Fusion Management and Systems Design*], Artech House, MA, (2012).
- [3] Munir, A., Blasch, E., Kwon, J., Kong, J., Aved, A., "Artificial Intelligence and Data Fusion at the Edge," *IEEE Aerospace and Electronic Systems Magazine*, vol. 36, no. 7, pp. 62-78, (2021).
- [4] Zheng, Y., Blasch, E., Liu, Z., [*Multispectral Image Fusion and Colorization*], SPIE, (2018).
- [5] Steinberg, A. N., Bowman, C. L., White, F. E., et al., "Evolution of the JDL Model," *ISIF Perspectives on Information Fusion*, 6 (1), 36-40, (2023).
- [6] Darema, F., et al. (eds.), [*Handbook of Dynamic Data Driven Applications Systems, Vol. 2*], Springer, (2023).
- [7] Blasch, E., "JDL Model (III) Updates for an Information Management Enterprise," in [*Multisensor data fusion: from algorithms and architectural design to applications*], Fourati, H., CRC press (2016).
- [8] Harbison-Moss, K. A., "Maintaining current Status in a Time-Constrained Knowledge-based System Characterized by Continuously Incoming Temporal Data (Truth Maintenance, Real-time), PhD Dissertation, Univ. Texas at Arlington, (1986).
- [9] MacMillan, J., Entin, E. B., Serfaty, D., et al., "Operator Reliance on Automated Support for Target Recognition," *Proc. of the Human Factors and Ergonomics Society Annual Meeting*, Volume 38, Issue 19, (1994).
- [10] Blasch, E., Li, X., Chen, G., Li, W., "Image Quality Assessment for Performance Evaluation of Image fusion," *Int'l Conf. on Info Fusion*, (2008).

- [11] Mendoza-Schrock, O., Patrick, J. A., et al., "Video Image Registration Evaluation for a Layered Sensing Environment," *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, (2009).
- [12] Blasch, E., Seetharaman, G., Palaniappan, K., et al., "Wide-Area Motion Imagery (WAMI) Exploitation Tools for Enhanced Situation Awareness," *IEEE Applied Imagery Pattern Recognition Workshop*, (2012).
- [13] Liu, Z., et al., "Fusing Synergistic Information from Multi-sensor Images: An overview from Implementation to Performance Assessment," *Information Fusion*, Vol. 42, pp. 127-145, (2018).
- [14] Blasch, E., Schuck, T., Gagne, O.B., "Trusted Entropy-Based Information Maneuverability for AI Information Systems Engineering," In: Lawless, W.F., et al. (eds.) [*Engineering Artificially Intelligent Systems*]. Lecture Notes in Computer Sci., Vol 13000. Springer, Cham. (2021).
- [15] Schuck, T., et al., "Information Maneuverability and the Transformation of the Warfighting Environment," *IEEE/AIAA Aerospace*, (2021).
- [16] Wei, J., Ardiles-Cruz, E., Panasyuk, A., et al., "Effective Damage Data Generation by Fusing Imagery with Human Knowledge Using Vision-Language Models," *IEEE NAECON*, (2025).
- [17] Blasch, E., Nagy, J., Aved, A., Pottenger, W. M., Schneider, M., et al., "Context aided Video-to-Text Information Fusion," *Int'l. Conf. on Information Fusion*, 2014.
- [18] Hammoud, R. I., Sahin, C. S., et al., "Automatic Association of Chats and Video Tracks for Activity Learning and Recognition in Aerial Video Surveillance," *Sensors*, 14, 19843-19860, (2014).
- [19] Ni, B., Liu, Z., Lei, Y., et al. "Towards trustworthy retrieval augmented generation for large language models: A survey," arXiv preprint arXiv:2502.06872, (2025).
- [20] Ni, B., Wang, Y., Cheng, L., et al., "Towards Trustworthy Knowledge Graph Reasoning: An Uncertainty Aware Perspective," *AAAI*, (2025).
- [21] Nikouei, S. Y., Chen, Y., Aved, A., et al., "I-SAFE: Instant Suspicious Activity identification at the Edge using Fuzzy Decision Making," *IEEE/ACM Symposium on Edge Computing conference*, Nov. (2019).
- [22] Liu, J., Mu, H., Vakil, A., Ewing, R., et al., "Human Occupancy Detection via Passive Cognitive Radio," 20, 4248; *Sensors*, (2020).
- [23] Yuan, L., Andrews, J., Mu, H., et al., "Interpretable Passive Multi-modal Sensor Fusion for Human Identification and Activity Recognition," *MDPI Sensors*, 22, 5787, (2022).
- [24] Cominelli, M., Gringoli, F., Kaplan, L. M., et al., "Neuro-Symbolic Fusion of Wi-Fi Sensing Data for Passive Radar with Inter-Modal Knowledge Transfer," *International Conference on Information Fusion*, (2024).
- [25] Cotti, L., Lavazza, L., Cominelli, M., et al., "Towards Causally Interpretable Wi-Fi CSI-Based Human Activity Recognition with Discrete Latent Compression and LTL Rule Extraction," *International Conf on Information Fusion*, (2026).
- [26] Panasyuk, A. et al., "Extraction of Semantic Activities from Twitter Data," *Semantic Tech. for Intelligence, Defense, and Security*, (2013).
- [27] Millar, D., Braines, D., et al., "Semantically-guided acquisition of trustworthy data for information fusion," *Int'l Conf. on Information Fusion*, (2021).
- [28] Shen, D., et al., "Adaptive Markov Game Theoretic Data Fusion Approach for Cyber Network Defense," *IEEE MILCOM*, (2007).
- [29] Yu, W., Xu, G., Pham, K. D., et al., "A Framework for Cyber-Physical System Security Situation Awareness," *Principles of Cyber-Physical Systems: An Interdisciplinary Approach*, Roy, S., Das, S.K., (eds.), Cambridge University Press, (2020).
- [30] Boicu, M., et al., [*AAAI FSS-21: Artificial Intelligence in Government and Public Sector Proceedings*]. arxiv.2112.05614, (2021).
- [31] Zheng, Y., Blasch, E., Liu, Z., [*Multispectral Image Fusion and Colorization*], SPIE, (2018).
- [32] Blasch, E., Liu, Z., Zheng, Y., "Advances in Deep Learning for Infrared Image Processing and Exploitation," *Proc. SPIE 12107*, (2022).
- [33] Elishkov, R., Weinstein, M., Fraenkel, R., et al., "SWIFT EI: the world's first SWIR event-based sensor," *Proc. SPIE 13454*, (2025).
- [34] Majumder, U., et al., [*Deep Learning for Radar and Communications Automatic Target Recognition*], Artech House, (2020).
- [35] Wang, T., Zhu, Z., et al., "Bio-Inspired Adaptive Hyperspectral Imaging for real-Time Target Tracking," *IEEE Sensors Journal*, Vol. 10, No. 3, pp. 647-654, (2010).
- [36] Guo, H., Schrader, P. T., et al. "Enhancing Multi-modal Automatic Target Recognition using Out-of-Distribution Exploitation (MATRODE)," *IEEE CVPR (PBVS)*, (2025).
- [37] Liu, S., Liu, H., John, V., et al., "Enhanced Situation Awareness through CNN-based Deep MultiModal Image Fusion," *Optical Engineering*, 59(5): 053103, (2020).
- [38] Xu, R., Chen, Y., et al., "A Federated Capability-based Access Control Mechanism for Internet of Things (IoTs)," *Proc SPIE*, vol. 10641, (2018).
- [39] Kahler, B., Blasch, E., "Predicted Radar/Optical Feature Fusion Gains for Target Identification," *Proc. IEEE Nat. Aerospace Elect. Conf.*, (2010).
- [40] Vakil, A., Liu, J., Zulch, P., et al., "A Survey of Multimodal Sensor Fusion for Passive RF and EO information Integration," *IEEE Aerospace and Electronic Systems Magazine*, 36(7): 44-61, (2021).
- [41] Fitwi, A., Chen, Y., Zhu, S., et al., "Privacy-Preserving Surveillance as an Edge Service Based on Lightweight Video Protection Schemes Using Face De-Identification and Window Masking" *Electronics* 10, no. 3: 236, (2021).
- [42] Blasch, E., Aved, A., "Information systems with a deep VAULT," *Proc. SPIE 13479*, (2025).
- [43] Blasch, E., "Fusion Orchestration Guidelines (FOG) for Collaborative Computing and Network Data Fusion," *IEEE Nat. Aerospace and Electronics Systems Conf*, (2023).

- [44] Munir, A., Kwon, J., Lee, J. H., et al., “FogSurv: A Fog-Assisted Architecture for Urban Surveillance Using Artificial Intelligence and Data Fusion,” *IEEE Access*, 9:111938-111959, (2021).
- [45] Wu, R., Liu, B., et al., “A Container-based Elastic Cloud Architecture for Pseudo Real-time Exploitation of Wide Area Motion Imagery (WAMI) Stream,” *J. of Signal Processing Sys.*, 88(2): 219-231, (2017).
- [46] Blasch, E., Cruise, R., Aved, A., Majumder, U., Rovito, T., “Methods of AI for Multimodal Sensing and Action for Complex Situations,” *AI Magazine*, 40(4):50-65, (2019).
- [47] Darema, F., et al., [*Dynamic Data Driven Applications Systems: Third International Conference, DDDAS 2020, Boston, MA, USA, October 2-4, 2020, Proceedings*], Springer, (2020).
- [48] Blasch, E., Kahler, B., “Multiresolution EO/IR Target Tracking and Identification,” *Int. Conf. on Info Fusion*, (2005).
- [49] Connare, T., et al., “Group IMM tracking utilizing Track and Identification Fusion,” *Proc. of the Workshop on Estimation, Tracking, and Fusion; A Tribute to Yaakov Bar Shalom*, 205-220, (2001).
- [50] Yang, C., et al., “Fusion of Tracks with Road Constraints,” *J. of Advances in Information Fusion*, 3(1):14-32, (2008).
- [51] Van Eeden, W. D., de Villiers, J.P., Berndt, R.J., et al., “Micro-Doppler radar classification of humans and animals in an operational environment,” *Expert Systems With Applications*, Vol. 102, (2018).
- [52] Bin, J., Zhang, R., Du, S., et al., “Improved Object Detection in Thermal Imaging Through Context Enhancement and Information Fusion: A Case Study in Autonomous Driving,” *NeurIPS (Neural Information Processing Systems)*, Autonomous Driving, (2021).
- [53] Merkel, C., Ororbia, A. G., “Contrastive Learning in Memristor-based Neuromorphic Systems,” arxiv.org/pdf/2409.10887, (2024).
- [54] IDS, “Beyond the frame rate,” 2025, accessed at [/www.ids-imaging.us/technical-articles-details/items/beyond-frame-rate.html](http://www.ids-imaging.us/technical-articles-details/items/beyond-frame-rate.html), (2026)
- [55] Blasch, E., Bohn, R., Gato, J., et al., “Future Direction of DDDAS/InfoSymbiotics and Collaborations with Related Initiatives,” International Conference on Dynamic Data Driven Applications Systems, (2020).
- [56] Blasch, E.P., Darema, F., Bernstein, D., “Introduction to the Dynamic Data Driven Applications Systems (DDDAS) Paradigm. In: Blasch, E.P., et al. (eds.). [*Handbook of Dynamic Data Driven Applications Systems, Vol 1 2nd Ed.*], Springer, (2022).
- [57] Ali-Akbarpour, H., Moori, A., Khorramdel, J., et al., “Emerging Trends and Applications of Neuromorphic Dynamic Vision Sensors: A Survey,” *IEEE Sensors Reviews*, vol. 1, pp. 14-63, (2024).
- [58] Sivilotti, M. A. [*Wiring considerations in analog VLSI systems, with application to field-programmable networks*], California Institute of Technology, (1991).
- [59] Kogler, J., Sulzbachner, C., Humenberger, M., Eibensteiner, F., “Address-event based stereo vision with bio-inspired silicon retina imagers,” *Advances in theory and applications of stereo vision*, pp. 165–188, (2011).
- [60] Gallego, G., Delbruck, T., Orchard, G., et al., “Event-based vision: A survey,” *IEEE transactions on pattern analysis and machine intelligence*, vol. 44, no. 1, pp. 154–180, (2020).
- [61] Huang, K., Zhang, S., Zhang, J., Tao, D., “Event-based simultaneous localization and mapping: A comprehensive survey,” *arXiv preprint arXiv:2304.09793*, (2023).
- [62] Jawaid, M., Elms, E., Latif, Y., Chin, T.-J., “Towards bridging the space domain gap for satellite pose estimation using event sensing,” *IEEE International Conference on Robotics and Automation (ICRA)*. pp. 11866–11873, (2023).
- [63] Rebecq, H., Gehrig, D., Scaramuzza, D., “Esim: an open event camera simulator,” in *Conference on robot learning*. PMLR, pp. 969–982, (2018).
- [64] Shi, X., Ling, H., et al., “Context-Driven Moving Vehicle Detection in Wide Area Motion Imagery,” *Int’l Conf on Pattern Recognition (ICPR)*, (2012).
- [65] Liang, P., Ling, H., et al., “Vehicle Detection in Wide Area Aerial Surveillance using Temporal Context,” *Int’l Conf. on Info Fusion*, (2013).
- [66] Steinberg, A. N., et al., “Adaptive Context Assessment and Context Management,” *Int’l. Conf. on Information Fusion*, (2014).
- [67] Snidaro, L., et al., [*Context-Enhanced Information Fusion: Boosting Real-World Performance with Domain Knowledge*], Springer, (2016).
- [68] Salerno, J. J., et al., “Evaluating algorithmic techniques in supporting situation awareness,” *Proc. of SPIE*, Vol. 5813, (2005).
- [69] Blasch, E., Kadar, I., Salerno, J., et al., “Issues and challenges of knowledge representation and reasoning methods in situation assessment (Level 2 Fusion),” *Proc. of SPIE*, Vol. 6235, (2006).
- [70] Yang, C., Bakich, et al., “Pose Angular-Aiding for Maneuvering Target Tracking,” *Int. Conf. on Info Fusion*, (2005).
- [71] Ling, H., Bai, L., et al., “Robust Infrared Vehicle Tracking Across Target Pose Change using L1 regularization,” *Int’l Conf. on Info Fusion*, (2010).
- [72] Palaniappan, K., Poostchi, M., et al., “Moving Object Detection for Vehicle Tracking in Wide Area Motion Imagery Using 4D Filtering,” *Int’l. Conf. on Pattern Recognition (ICPR)*, (2016).
- [73] Ali Akbarpour, H., Collins, J., et al. “Flexible Multicamera Virtual Focal Plane: A Light-Field Dynamic Homography Approach,” In: [*Scanning Technologies for Autonomous Systems*]. Springer, Cham., (2024).
- [74] Blasch, E., “Dynamic Data Driven Applications Systems (DDDAS) for Space Sensor Fusion,” *AIAA SCITECH Forum*, 1450, (2026).
- [75] Hanselman, P., Lawrence, C., Fortunano, E., et al., “Dynamic Tactical Targeting,” *Proc. of SPIE*, Vol. 5441, (2004).
- [76] Gao, J., Ling, H., et al., “Pattern of life from WAMI objects tracking based on visual context-aware tracking and infusion network models,” *Proc. SPIE*, Vol. 8745, (2013).
- [77] Zohuruzzaman, A. Q. M., Wamai, D., Feng, W., Khan, S., et al., “Highway Slope Monitoring using 3D Laser Scanning at Different Seasons,” *Proc. SPIE 13037*, (2024).

- [78] Shen, D., Chen, G., et al., "A Game Theoretic Data Fusion Aided Path Planning Approach for Cooperative UAV ISR," *IEEE Aerospace Conf.*, (2008).
- [79] Imai, S., et al. "Airplane Flight Safety Using Error-Tolerant Data Stream Processing," *IEEE Aero. and Elect. Sys. Mag.*, 32(4): 4–17, (2017).
- [80] Blasch, E., Paces, P., Leuchter, J., "Pilot Timeliness of Safety Decisions Using Information Situation Awareness," *IEEE/AIAA Digital Avionics Systems Conference*, (2014).
- [81] Paul, S., et al., "Formal Verification of Safety-Critical Aerospace Systems," in *IEEE Aero. and Elect., Sys. Magazine*, (2023).
- [82] Blasch, E., Breton, R., Valin, P., "Information Fusion Measures of Effectiveness (MOE) for Decision Support," *Proc. SPIE* 8050, (2011).
- [83] Benson, C., Holzinger, M., "Simulation and analysis of event camera data for non-resolved objects," *The Journal of the Astronautical Sciences*, 71(1):3, (2023).
- [84] Greaves, J. A., Scheeres, D. J., "Autonomous Information Gathering Guidance for Distributed Space Systems with Optical Sensors," American Control Conference (ACC), pp. 4826-4831, (2023).
- [85] Nkrumah, I., Moshrefizadeh, M., Tahri, O., et al., "EC-WAMI: Event Camera-Based Pose Optimization in Remote Sensing and Wide-Area Motion Imagery," *Sensors*, 24, 7493, (2024).
- [86] Malik, S. S., Moshrefizadeh, M., Tahri, O., et al., "EvSat3D: Satellite Pose Estimation and 3D Reconstruction with Event Camera," *IEEE Access*, 13: 130340-130352, (2025).
- [87] Ali-Akbarpour, H., Palaniappan, K., Seetharaman, G., "Parallax-tolerant aerial image georegistration and efficient camera pose refinement—without piecewise homographies," *IEEE Trans. Geosci. Remote Sens.*, 55(8): 4618–4637, Aug. (2017).
- [88] Jia, B., Pham, K., et al., "Space Object Classification Using Deep Neural Networks," *IEEE Aerospace Conf.*, (2018).
- [89] Blasch, E., Pham, K., Shen, D., Chen, G., "Orbital Satellite Pursuit-Evasion Game-Theoretical Control," *IEEE Int'l. Conf on Info. Sci., Sig. Processing and App. (ISSPA)*, (2012).
- [90] Liu, Z., Blasch, E., Liao, M., et al., "Digital Twin for Predictive Maintenance," *Proc. SPIE* 12489, (2023).
- [91] Dodson, J., Downey, A., et al., "High-rate structural health monitoring and prognostics: an overview," *Data Science in Engineering*, Volume 9, 213-217, Springer, Chm, (2022).
- [92] Vereen, A. B., Ogunniyi, E. A., et al., "Optimal Sampling Methodologies for High-rate Structural Twinning," *International Conference on Information Fusion (FUSION)*, (2023).
- [93] Laflamme, S., et al. "Roadmap: Integrating Artificial Intelligence in Structural Health Monitoring Systems," *Measurement Science and Technology*, 37: 103001, IOP Publishing, (2026).
- [94] Fuc, Y., Whethama, M., Downey, A. R.J., Yuana, L., Comert, G., "A Study of Online Melt Pool, Plume, and Spatter Tracking in Laser Powder Bed Fusion using DBSCAN," *Proc. SPIE*, Vol. 13438, (2025).
- [95] Liu, S., Gao, M., John, V., et al., "Deep Learning Thermal Image Translation for Night Vision Perception," *ACM Transactions on Intelligent Systems and Technology*, 12(1):1-18, Dec. (2020).
- [96] Ling, J., Feng, K., Wang, T., et al., "Data Modeling Techniques for Pipeline Integrity Assessment: A State-of-the-Art Survey," in *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1-17, (2023).
- [97] Yuan, J. et al., "DipDNN: Decomposed Invertible Pathway Deep Neural Networks," *ICLR Openreview.net/forum?id=YcJCzJzQT5*, (2024).
- [98] Yuan, J. et al., "DipDNN: Preserving Inverse Consistency and Approximation Efficiency for Invertible Learning," *SIGKDD, ACM Knowledge Discovery and Data Mining*, (2024).
- [99] Li, H., et al., "Adversarial twin neural networks: maximizing physics recovery for physical system," *ICLR, openreview.net/forum?id=7WVAI3dRwhR*, (2022)
- [100] Li, H., et al., "Distribution Grid Topology and Parameter Estimation Using Deep-Shallow Neural Network with Physical Consistency," *IEEE Transactions on Smart Grid*, Vol. 15, Issue 1, pp. 655-666, Jan (2024).
- [101] Shamsoshoara, A., Afghah, F., "Airborne Fire Detection and Modeling Using Unmanned Aerial Vehicles Imagery: Datasets and Approaches," In: Darema, F., et al. eds.) [*Handbook of Dynamic Data Driven Applications Systems*]. Springer, (2023).
- [102] Wei, J., Feng, W., et al., "Deep Learning Approach for Data and Computing Efficient Situational Assessment and Awareness in Human Assistance and Disaster Response and Battlefield Damage Assessment Applications," In: [*Dynamic Data Driven Applications Systems. DDDAS 2022*]. Lecture Notes in Computer Science, vol. 13984. Springer, Cham. (2024).
- [103] Luna, J., Robles, R., et al., "Energy-based MOR for Flexible Space Robotic Systems," *AIAA SCITECH Forum*, 0167, (2026).
- [104] Blasch, E., Sung, J., Nguyen, T., "Multisource AI Scorecard Table for System Evaluation," *AAAI FSS-20: Artificial Intelligence in Government and Public Sector*, (2020).
- [105] Cohen, M. C., Kim, N., Ba, Y., et al. "PADTHAI-MM: Principles-based approach for designing trustworthy, human-centered AI using the MAST methodology," *AI Magazine*, Vol. 46, Issue 1, e70000, Mar (2025).
- [106] Yang, X., Lin, J., et al., "On Situational Aware En-Route Filtering against Injected False Data in Cyber Physical Systems," in [*Situational Awareness in Computer Network Defense: Principles, Methods and Applications*], IGI Global, (2012).
- [107] Bao, Y., Shen, D., Chen, G., et al., "Requirements modeling of resilience-aware human-on-the-loop PNT of multiple UASs," *Proc. SPIE* 13062, (2024).
- [108] Bao, Y., Shen, D., Chen, G., et al., "Learning-based Resilience Optimization of Human-on-the-loop Multiple Unmanned Aerial System Positioning Using Mean Field Games," *Journal of Guidance, Control, and Dynamics*, 49(4), (2026).
- [109] Blasch, E., "Situation, Impact, and User Refinement," *Proc. of SPIE*, Vol. 5096, (2003).
- [110] Blasch, E., Darema, F., Metaxas, D., "Introduction to the DDDAS2024 Conference Infosymbiotics/DDDAS and AI: Towards Reliable AI," In: Blasch, E., et al. (eds.) [*Dynamic Data Driven Applications Systems. DDDAS/Infosymbiotics for Reliable AI 2024*]. Lecture Notes in Computer Science, vol. 15514. Springer, Cham., (2026).