Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 18 (2013) 1999 – 2007

Procedia
Computer Science

2013 International Conference on Computational Science

Dynamic Data Driven Applications System concept for Information Fusion

Erik Blasch[a]*, Guna Seetharaman[a], Kitt Reinhardt[b]

[a]Air Force Research Laboratory (AFRL/RIEA), 525 Brooks Rd., Rome, NY 13441, USA
[b]Air Force Research Laboratory (AFRL/RY), 2241 Avionics Cir., WPAFB, OH 45433, USA

Abstract

We present a framework of Information Fusion (IF) using the Dynamic Data Driven Applications Systems (DDDAS) concept. Existing literature at the intersection of these two topics supports environmental modeling (e.g., terrain understanding) for context enhanced applications. Taking advantage of sensor models, statistical methods, and situation-specific spatio-temporal fusion products derived from wide area sensor networks, DDDAS demonstrates robust multi-scale and multi-resolution geographical terrain computations. We highlight the complementary nature of these seemingly parallel approaches and propose a more integrated analytical framework in the context of a cooperative multimodal sensing application. In particular, we use a Wide-Area Motion Imagery (WAMI) application to draw parallels and contrasts between IF and DDDAS systems that warrants an integrated perspective. This elementary work is aimed at triggering a sequence of deeper insightful research towards exploiting sparsely sampled piecewise dense WAMI measurements – an application where the challenges of big-data with regards to mathematical fusion relationships and high-performance computations remain significant and will persist. Dynamic data-driven adaptive computations are required to effectively handle the challenges with exponentially increasing data volume for advanced information fusion systems solutions such as simultaneous target tracking and identification.

Selection and peer review under responsibility of the organizers of the 2013 International Conference on Computational Science

Keywords: Information Fusion; DDDAS; Cooperaive Sensing; Wide-Area Motion Imagery; target tracking; situation awareness

1. Introduction to DDDAS for Information Fusion

DDDAS is a concept where measurements form a symbiotic feedback control for applications with or without simulation augmentation [1, 2, 3]. As a control system, DDDAS dynamically uses collected data to (1)

* Corresponding author. Tel.: +1-315-330-2395.
E-mail address: erik.blasch@rl.af.mil.

1877-0509 © 2013 The Authors. Published by Elsevier B.V.
Selection and peer review under responsibility of the organizers of the 2013 International Conference on Computational Science
doi:10.1016/j.procs.2013.05.369

guide the measurement process and (2) choose among processing methods over a trade space of two or more interdependent factors. An application operating on sensed data can be thought of as an information fusion system made popular in the 1980s from the development of the Kalman Filter in the 1960s [4]. Information fusion, like DDDAS, seeks to reduce uncertainty through filtering past data, estimating current states, and predicting future needs such as that of simultaneously tracking and identifying a target [5, 6]. Using the DDDAS concept, current trends include information management, large volume data processing, and system software over an enterprise for real-world complex systems design [7]. DDDAS as a concept, supports the advanced systems-level processing needed for complex information fusion systems.

DDDAS since its inception has been applied to numerous areas where complex real-world conditions are not predetermined by the initialization parameters and initial static data [8, 9, 10]. Three common areas include environmental modeling, situation awareness, and systems-level applications. DDDAS *environmental modeling* includes oceans [11] and wild fires [12, 13]. Other examples include social services such as transportation [14], emergency medical response [15], and waste distribution [16]. Combining the above applications in a complex system could facilitate accurate weather prediction for emergency response as demonstrated by the Engineering Research Center for Collaborative Adaptive Sensing of the Atmosphere (CASA) formed by the National Science Foundation [17]. These applications for environmental assessment have similar goals of information fusion stochastic modeling for uncertainty assessment [18]. Even diverse applications such as cyber situational awareness have been a forum for DDDAS [19] and IF. These applications are similar to data registration and terrain environmental modeling frequent in the information fusion literature.

With these developments in DDDAS, further research continued to explore these areas while more broadly applying the DDDAS concept to different applications. Hurricane modeling for weather and climate prediction [20] and emergency response [21] cross research in information fusion where different events are modeled for *situational awareness*. For example, not only sensor data from the weather, but also multi-modal imagery [22]. Multi-modal imagery can be used for information fusion object tracking, classification, and identification that supports situation assessment, awareness, and understanding.

Enhancements were made to increase the fidelity of DDDAS modeling and simulation for forest fires [23], civil infrastructure, and traffic management [24]. *Systems-level concepts* were demonstrated for manufacturing [25] and supply chain modeling [26]. Finally, by understanding the system level situation, one can predict the threat and trust in an system [27]. Consistent DDDAS applications in the last decade are tied to systems-level environmental modeling. Areas of water ecology and infiltration [28, 29, 30] are important for society (e.g., health), the military (e.g., protection), and systems response (e.g. logistics). DDDAS continues to be a method for a modeling a top international health concern of surface water [31] and ground water infiltration [32]. Based on these developments and successes of DDDAS for environmental and systems-level complex modeling, its merits consideration in information fusion.

The rationale and potential benefits of DDDAS can enhance information fusion (IF) processes. DDDAS processes can be driven by batch-level *statistical analysis* would amortize the temporal variations of observed wide-sense stationary processes into power-spectral densities or probabilistic networks. DDDAS *control* effectively steers computations over a current measurements based on associations extracted from the previous ones. Such methods are used in practice to effectively allocate computational resources by matching the expected entropies of localized information content as a function of the multidimensional space that the observations span. For example, in atmospheric modeling over vast areas, turbulent flows would require high resolution over small regions, and laminar-flow dominated regions will accept coarser computations without a noticeable degradation or artifacts. Then, the IF challenge is how to let the data dictate a dynamic assessment of an effective processing of the observed data. While many classic works have been published on multi-grid techniques based on batch-mode and model-driven decomposition strategies, the ***data-driven dynamic partitioning strategies*** remain a topic of intense interest in many applications. For example, the diversity of hard (i.e., physics based video) and soft (i.e., human based text) data may be dynamically available for IF. A human must effortlessly use in such hard-soft data instances that do not always lend themselves for direct representation by computers. Capturing feature-rich associations are critical to impact overall result, which need to be represented in a manner that can be easily integrated to steer and catalyze essential inferences.

In this paper, we will consider a spatio-temporal information relations, commonly used in computer vision, to forecast the wide-area motion image analysis as a DDDAS problem. The diverse applications of DDDAS show promise, such that insights can be cooperatively gained from merging the benefits of DDDAS and information fusion such as sensor fusion, social and behavioral modeling, cognitive measurements, and mission awareness. For example, a merging of data mining [33] as an information fusion technique with that of DDDAS information management [34] are current trends. Applications include complex systems that are sometimes difficult to model; however with increased multi-modal sensing, big data cloud techniques, and enterprise architectures, DDDAS paves the way for information fusion systems management.

Section 2 overviews information fusion cast in terms of DDDAS. Section 3 presents an example of WAMI integrated multi-modal sensing, processing, and exploitation. Section 4 concludes the paper as a way ahead for continued exploration of merging DDDAS and information fusion techniques.

2. Information Fusion

Information fusion has been applied to many applications. One commonly accepted model is the Data Fusion Information Group (DFIG) model [35] (shown in Figure 1) originally developed for military systems, but adopted by the International Society of Information Fusion (www.isif.org) as a common processing framework. The levels (L) determine the processing in the system such as L0 data registration, L1 object tracking and identification assessment [5], L2 situation awareness [36, 37] and L3 impact assessment [38]. The complementary control levels are: L4 sensor management, L5 user refinement [39], and L6 mission management. Together, these levels of processing could be represented in an DDDAS framework.

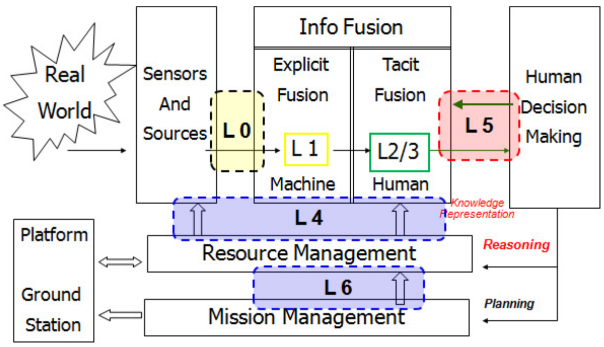

Fig. 1. Data Fusion Information Group Model (L = Level)

2.1. Information fusion as a systems application

As *data* and sensors measurements become more available, it is important that the models and system software be scalable, agile, and provide data relevance to user queries. User refinement [40] includes focusing on the interaction of an operator with a system to achieve mission needs. For example, choosing the correct sensor mode requires the modeling and adaptation of the systems to deliver the correct information in response to a query. When the user requests objects information (L1) within a situation (L2); environmental considerations need to be accounted for such as the time of operation (e.g., day or night), weather conditions (e.g., clouds), and geographical information (e.g., terrain). By correctly modeling the environmental situation, the correct multimodal visual or infrared sensor (L4) can deliver the optimal response. Inherent in this example is the fact that DDDAS solutions are needed for accurate environmental modeling to achieve desired objectives and *data-driven dynamic partitioning strategies*. To achieve the desired results requires advances in enterprise architectures (shown in Figure 2) that we contend is afforded by advancements in DDDAS.

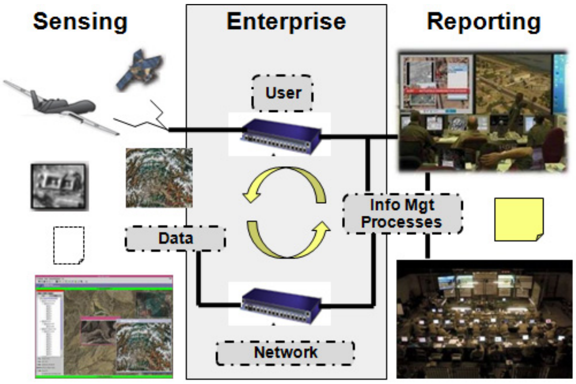

Fig. 2. Information Fusion in the Enterprise.

As the information fusion system composes an enterprise, the software needs to be able to provide *dynamic* responses. Examples includes tasking sensors on mission platforms [41] for resource coordination. DDDAS is a control architecture which supports data fusion, performance prediction, and sensor management for target tracking, recognition, and identification [42]. Accurate *statistical modeling* of the sensors and the environment support that objectives are met in a timely and effective manner. One recent example of both information fusion solutions and DDDAS applications is mission coordination and cooperative sensing for unmanned aerial vehicles (UAVs) [43]. Also, UAVs can be coordinated with sensors on the ground [44] that require terrain modeling. Together, DDDAS environmental modeling of the weather for the UAVs and the terrain information for the ground sensors would aid in the analysis of the complete system.

2.2. DDDAS mapped to the information fusion processing levels

Using our multimodal cooperative sensing example, we are interested in simultaneous target tracking and identification (STID). Multi-modal measurements could be from infrared, visual, and/or wide-area motion imagery (WAMI). One recent complex challenge is large data wide-area motion imagery (WAMI) [45]. WAMI processing with information management supports moving intelligence [46]. Complications of real-time WAMI sensor processing include a low frame rates [47] and mappings to geospatial intelligence systems [48] such as environmental (e..g., terrain modeling). Together, DDDAS and IF support enhanced situation awareness [49] for cooperative control of multimodal sensors as depicted in Figure 3.

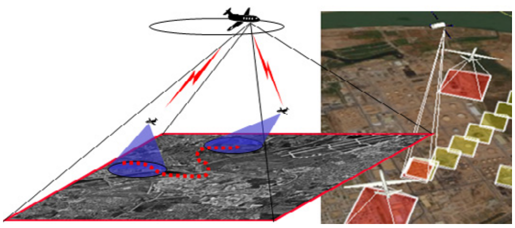

Fig. 3. Wide Area Motion Imagery (WAMI) data.

Accurate statistical modeling is needed of the environment, sensor, and target data to support the mathematical algorithms as shown in Table 1. Note that identification includes composing object recognition and kinematic data for threat assessment of friend, foe, and neutral (FFN) affiliation.

Table 1. Information Fusion Processing Levels as DDDAS measurement, models, and mathematical solutions

Info Fusion / DDDAS Application	Measurement	Model	Algorithm
Level 0 – Data Registration	Pixels	Terrain	Scale-Invariant Feature Transform (SIFT)
Level 1 – Object Assessment	Kinematic/Features	Kinematic/Target	Kalman Filter (KF), Joint-Belief Data Association Filter (JBDAF)
Level 2 – Situation Assessment	Object Groups	Behavioral	Social Network Analysis (SNA)
Level 3 – Impact Assessment	Threat (FFN)	Intent/Allegiance	(Bomb) Damage Assessment (BDA)
Level 4 – Sensor Management	Look angles	Camera	Affine Transformation
Level 5 – User Refinement	Head-mounted display	Cognitive	Eye Tracker, Fitts' Law
Level 6 – Mission Management	Objectives	Goal-driven	Reinforcement Learning (RL)

.

3. Application – Interactive Multi-Modal Sensing Processing and Exploitation

There are many attributes which compose an IF system of which we are interested in an integrated multimodal sensing, processing, and exploitation (IMMSPE) technique. DDDAS is based on applications modeling, mathematics, and systems software all of which are needed for cooperative sensing. For multimodal cooperative sensing, there are many issues from which theoretical modeling supports simulations and measurements. First, with the large amount of motion imagery (i.e., big data problem), there is a need for cooperative sensing for real-time applications. Second, for meeting user demands, there is a need for multimodal analysis (i.e., Data to Decision problem). Figure 4 presents our DDDAS architecture that maps to the information fusion processing levels for Senor, User, and Mission (SUM) management.

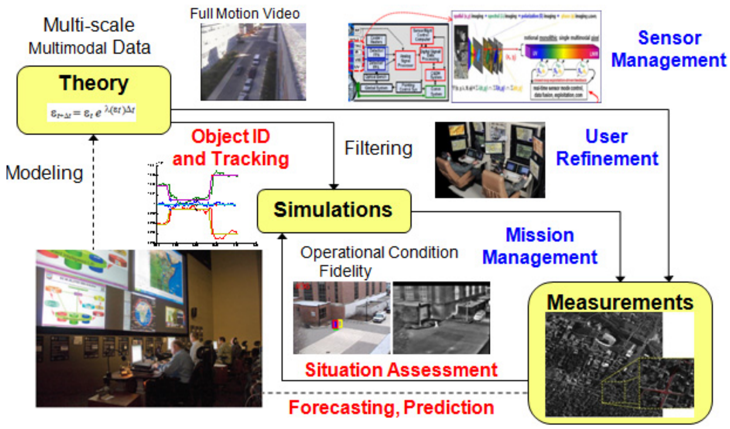

Fig. 4. DDDAS Application of Multimodal Cooperative Sensing

On the top in Figure 4, theory aids in supporting tracking and identifying objects for sensor data management. On the bottom, real-time measurements aid system software and sensor collections for mission management. In the middle, the cooperation of data (including environment, target, and sensor models) coordinates different multimodal imagery collections for user refinement of data products. For mathematical, simulation, and software applications, there is a focus on multiscale multimodal approaches. Here multimodal includes [from left to right] (1) multi-cognition of different users, (2) multi-location of UAVs and ground platforms collecting full-motion video, and (3) multi-frequency sensors such as WAMI, Infrared, and Visual imagery. Future considerations include multi-intelligence data (multi-INT) to complement the imagery (IMINT) such as overhead geographical (GEOINT) terrain and weather modeling. Using this framework for our DDDAS application, we next briefly describe the mathematical modeling, statistical analysis, and the systems software for dynamic imagery-based edge detection of static objects.

3.1. WAMI Object Edge Detector (WOED)

Edge detection is one of most fundamental operations in image analysis. In it is simplest form, it detects the presence of spatial discontinuity. A rich set of operators exist in standard textbooks, to detect, filter, extract and group edge segments representing lines, contours etc, but *data-driven dynamic partitioning strategies* are needed. Suffice it to say that these filters are estimating the existence of an edge from an image data which include artefacts introduced in the imaging process. The filter results contain latent uncertainties left unmitigated by these unconstrained optimal estimators. It is worth noting that edges in this context would originate due to roads, lane-markings, lamp-posts, bill-boards, and buildings in urban imagery shown in Figure 5. Information fusion of contextual knowledge such as geographic directions of a road-segment, or orientation of a building can thus be used to select among the filters. A class of operators based on Gabor filters extract edges in an evidence accumulation/validation mode. Such operators select a specific filter from a bank of filters, each tuned to be highly sensitive to discontinuities along preferred orientation. A more nuanced view would seek the dynamic range of the *a priori* orientations including representations to steer these edge detectors. For example, we define an attractor point as a unique point on the 2D image characterized by the context-based 3-D direction cosine of the line, perspective imaging geometry, and the exact senor location and orientation [50].

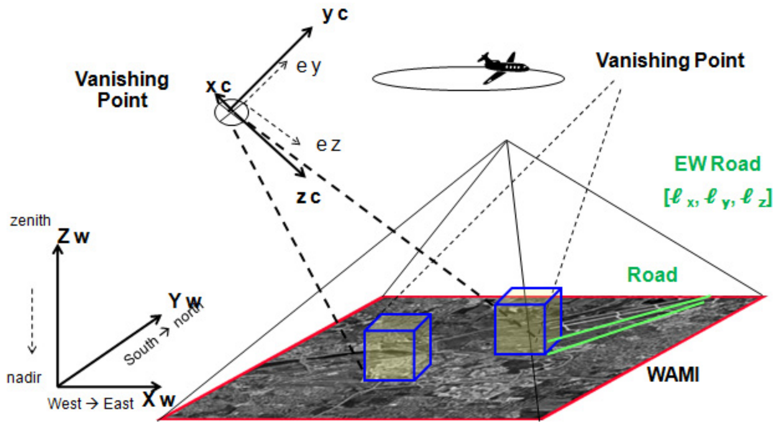

Fig. 5. WAMI Edge Detection, contextual information such as location, height, and orientation of buildings and roads can be fused into quantifiable information once the camera position is known.

Image registration is another fundamental operator in image analysis that aligns two or more images in a information processing task. The simplest manifest is made of two time-separated images of a dynamic scene, or two stereo images of a static scene observed from distinct relative-directions. Then, by definition, image registration seeks a one-to-one non-bijective mapping made of maximal (size) simply-connected sets of pixels between the images. When the 3D features underlying such a patch represent a planar surface, the spatial relation between corresponding connected sets can be characterized as an affine mapping (or homography) for orthographic and perspective imaging applications [51, 52]. Contextual information such as height, location and orientation of buildings can be suitably captured and exploited as a priori information to facilitate the image registration. Registration is a fundamental and essential step to consolidate spatial information across multiple views, or temporal information across video image sequences. Using both edge detectors and registration techniques for stochastically varying image collections, DDDAS can support context-based image retrieval over systems-level analysis and modelling.

3.2. WAMI Context-Based Image Retrieval

In complex scenarios, made up of more than one surface, as is the case for even a vast ground with one building, each image will be comprised of at least two distinct patches, or four patches, in general. Contrary to the common view, registration between a pair of WAMI images of a single building in fact involves at least two distinct homographies and at most four distinct homographies. The challenge is to segment the images, establish region correspondence, and estimate [51] homographies. Therein lies a *data driven portioning* of the data-space, to get past the Rubicon of registration, so that higher-level inferences can be derived. Additionally, when three or more landmarks are identified [53] in the observed image, the net information can be captured constrain or mitigate uncertainties in camera orientation measurements as well as the camera-location [54].

For edge detection in the forward direction, there are an infinite number of possibilities, so we are not able to comprehensively evaluate. However, for the asymmetric case, we can rule out the possibilities through contextual analysis (e.g. pixel uncertainties due to weather contaminants) to determine the edges. With advanced DDDAS (modelling) and information fusion (registration), the exploitation of the imagery can support activity analysis. For example, a car moving on a road gives both the change detection for the car and a cue as to the road location. The goal of combing DDDAS with information fusion is to use the WAMI camera model and terrain models (even simulated) from which to quickly extract edges in an image form dynamic scenes. Using the combined DDDAS-IF methodology, object detection would be quicker that a brute force method in analysis that is supported by context models, simulations, and mathematical software optimization.

4. Conclusions

Future trends for both DDDAS and information fusion include big data, multi-modal sensing, information management, and cloud computing. In this paper, we have shown a need for the synergistic developments in DDDAS and information fusion for Wide-Area Motion Imagery modeling. The benefits so DDDAS inspired modeling and applications software development complement multimodal cooperative sensing through environmental modeling. We are exploring DDDAS for a variety of multimodal and multiscale imagery analysis such as that of airborne multi-intelligence sensing as well as ground based visual [55, 56] and TeraHertz [57, 58] imagery sensing and advanced image processing in a cloud environment [59].

Acknowledgements

The authors appreciate the discussions and motivation of advancements from DDDAS towards information fusion solutions from Dr. Frederica Darema. This work was supported by the United States Air Force and thus free of copyright of the publisher. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the Air Force.

References

[1] http://www.dddas.org/

[2] DDDAS Workshop Groups. 2000. *Creating a dynamic and symbiotic coupling of application/simulations with measurements/experiments*. NSF DDDAS 2000 Workshop. Available via http://www.nsf.gov/cise/cns/dddas/ [accessed Jan 2013].

[3] Darema, F., 2005. "Grid Computing and Beyond: The Context of Dynamic Data Driven Applications Systems," *Proceedings IEEE*, **93**(3), p. 692-697.

[4] Waltz, E., Llinas J., *Multisensor Data Fusion*, Artech House, 1990.

[5] Blasch, E. P., Hong, L., 1998."Simultaneous Identification and Track Fusion," *IEEE Conf. on Dec. Control.*

[6] Blasch, E., *Derivation of A Belief Filter for High Range Resolution Radar Simultaneous Target Tracking and Identification*, Ph.D. Dissertation, Wright State University, 1999.

[7] E. Blasch, E. Bosse, and D. A. Lambert, 2012. *High-Level Information Fusion Management and Systems Design*, Artech House.

[8] Knight, D., 2003. "Data driven design optimization methodology—a dynamic data driven application system," New York: Springer Verlag; pp. 329–336.

[9] Darema, F., 2004. "Dynamic Data Driven Applications Systems: A New Paradigm for Application Simulations and Measurements. Computational Science." *ICCS 2004, Lecture Notes in Computer Science series*, 3038, 662–669.

[10] Darema, F., 2005. "Dynamic data driven applications systems: New capabilities for application simulations and measurements," *Lecture Notes in Computer Science* 3515, p. 610–615, 2005.

[11] Patrikalakis, N.M., McCarthy, J. J., Robinson, A. R., *et al*., 2004. "Towards a Dynamic Data Driven System For Rapid Adaptive Interdisciplinary Ocean Forecasting,"F. Darema (ed.), *Dynamic Data Driven Applications Systems*, Kluwer Academic Pub., p. 1-16.

[12] Chen M., *et al*., 2004."Dynamic data driven wildfire modeling," F. Darema (ed.) *Dynamic Data Driven Applications Systems*. Kluwer Acadmec Publishers.

[13] Chen M., *et al*., 2005."Towards a Dynamic Data Driven Application System for Wildfire Simulation. In V.S. Sunderam et al. (eds.) Computational Science, *Proc. Int'l Conf. on Computational Science (ICCS), Lecture Notes in Computer Science*. 3515, p. 632-639.

[14] Fujimoto R. M., Guensler, R. Hunter, M. et. al, 2004."Dynamic data driven application simulation of surface transportation systems," *ICCS 2004, Part III, LNCS* 3993:425-432. Berlin: Springer-Verlag.

[15] Gaynor M., Seltzer M., Moulton, S., Freedman, J., 2005. "A dynamic, data-driven, decision support system for emergency medical services," In *Proc. of the Int'l Conf. on Computational Science (ICCS),* LNCS 3515, Springer-Verlag, Berlin, p. 703–711.

[16] Parashar, M., Matossian, V., Klie, H., et. al., 2006."Towards Dynamic Data-Driven Management of the Ruby Golch Waste Repository," In *Proc. of the Int'l Conf. on Computational Science (ICCS).*

[17] Brotzge, J., Droegemeier, K. K., McLaughlin, D. J., 2006. "Collaborative adaptive sensing of the atmosphere (CASA): new radar system for improving analysis and forecasting of surface weather conditions," *J Transp Res Board*, p. 145–151.

[18] Douglas, C. C., Efendiev, Y., Ewing, R., Ginting, V., and Lazarov, R., 2006. "Dynamic Data Driven Simulations in Stochastic Environments," *Computing*, 77(4):321–333.

[19] Mahinthakumar, K., von Laszewski, G., Ranjithan, R., et. al, 2006. "An adaptive cyberinfrastructure for threat management in urban water distribution systems," *Int'l Conf. on Computational Science (ICCS),* LNCS 3993, p. 401–408.

[20] Allen, G., 2007, "Building a Dynamic Data Driven Application System for Hurricane Forecasting," *Int'l Conf. on Computational Science (ICCS),* LNCS, vol. 4487, p. 1034–1041. Springer, Heidelberg.

[21] Madey, G., Barabási, A. L., Chawla, N., Gonzalez, M.., 2007. "Enhanced situational awareness: Application of DDDAS concepts to emergency and disaster management," *Int'l Conf. on Computational Science (ICCS)*.

[22] Ononye, A.E., Vodacek, A., and Saber, E., 2007. "Automated extraction of fire line parameters from multispectral infrared images, *Remote Sensing of Environment* 108:179-188.

[23] Denham, M., Cortes, A., Margalef, T., Luque, E., 2008. "Applying a Dynamic Data Driven Genetic Algorithm to Improve Forest Fire Spread Prediction," M. Bubak et al. (Eds.): ICCS 2008, LNCS 5103, pp. 36–45, Springer-Verlag Berlin Heidelberg.

[24] Huang, Y., and A. Verbraeck, 2009. "A Dynamic Data-Driven Approach For Rail Transport System Simulation," In *Proc. IEEE Winter Simulation Conference,* 2553–2562.

[25] Douglas, C., L.Deng, Efendiev, Y., *et al*., 2010. "Advantagesof multiscale detection of defective pills during manufacturing," HPCA2010, LNCS, vol. 5938, pp. 8-16. Springer-Verlag Berlin Heidelberg.

[26] Celik, N., Lee, S., Vasudevan, K., Son, Y., 2010. DDDAS-based multi-fidelity simulation frameworkfor supply chain systems, *IIE Transaction*, 42/5:325-341.

[27] Onolaja, O., Bahsoon, R., Theodoropoulos, G., 2010. "Conceptual framework for dynamic trust monitoring and prediction," *Procedia Computer Science* 1(1), 1241– 1250.

[28] Stonestrom, D.A., Blasch, K.W., 2003. "Determining temperature and thermal properties for heat-based studies ofsurface-water ground-water interactions," In Heat as a Tool for Studying the Movement of Ground Water Near Streams, ed. D.A. Stonestrom and J. Constantz, 73–80. *USGS Circular* 1260. Reston, Virginia: USGS.

[29] Blasch, K., Ferre, P., Hoffmann, J., Fleming, J. 2006, "Relative contributions of transient and steady-state infiltration fluxes during ephemeral streamflows," *Water Resour. Res*., 42, W08405, doi:10.1029/ 2005WR004049.

[30] Blasch, K., Constantz, J., and Stonestrom, D. A., 2007. "Thermal methods for investigation ground-water recharge," *U.S. Geol. Surv. Prof. Pap*., 1703, 353– 376.
[31] Ouyang, Y., Luo, S. M., Cui, L. H., *et al*., 2011, "Estimation of real-time N load in surface water using dynamic data-driven application system,"*Ecological Engineering*, Elsevier.
[32] Yu, H., Douglas, C. C., Ogden, F. L., 2012. "A new Application of Dynamic Data Drive System in the Talbot-Ogden model for Groundwater Infiltration," *Procedia Computer Science*, Elsevier.
[33] Waltz, E. L. 1998. "Information understanding: integrating data fusion and data mining processes," *Int. Symp on Circuits and Systems*, Vol. 6.
[34] Metzler, J. M., Linderman, M., H., Seversky, L. M., 2009. "N-CET: Network-Centric Exploitation and Tracking," *IEEE Military Communication (MILCOM) conference*.
[35] Blasch, E., Plano, S., 2005. "DFIG Level 5 (User Refinement) issues supporting Situational Assessment Reasoning," *Int. Conf. on Info Fusion*,
[36] Salerno, J., Blasch, E., Hinman, M., Boulware, D., 2005. "Evaluating algorithmic techniques in supporting situation awareness," *Proc. of SPIE,* Vol. 5813.
[37] Blasch, E., Kadar, I., Salerno, J., Kokar, M. M., Das, S., *et. al*., 2006. "Issues and Challenges in Situation Assessment (Level 2 Fusion)," *J. of Adv. in Information Fusion,* Vol. 1, No. 2, pp. 122 - 139, Dec.
[38] Shen, D., Chen, G., Blasch, E., and Tadda, G., 2007. "Adaptive Markov Game Theoretic Data Fusion Approach for Cyber Network Defense," *IEEE Military Communications Conf (MILCOM)*, Oct.
[39] Blasch, E., 2006. "Level 5 (User Refinement) issues supporting Information Fusion Management" *Int. Conf. on Info Fusion*.
[40] E. Blasch, *et al*., 2002. "JDL Level 5 Fusion model 'user refinement' issues and applications in group Tracking," *Proc. SPIE,* 4729.
[41] Blasch, E., Kadar, I., Hintz, K., *et. al*., 2008. "Resource Management Coordination with Level 2/3 Fusion Issues and Challenges,"*IEEE Aero. and Elect. Sys. Mag.,* Vol. 23, No. 3, pp. 32-46, Mar.
[42] Blasch, E., Moses, R., Castanon, D., Willsky, A., Hero, A., 2008. "Integrated Fusion, Performance prediction, and sensor management for Automatic Target recognition," *Int. Conf. on Info Fusion*.
[43] Shen, D., Chen, G., Cruz, J., Blasch, E., 2008. "A game Theoretic Data Fusion Aided Path Planning Approach for Cooperative UAV Control," *IEEE Aerospace Conf.*
[44] Srivasta, A., Wen, Y., Hendrick, E., et. al, 2011, "Information Fusion for Object & Situation Assessment in Sensor Networks," *IEEE American Control Conf.*
[45] Mendoza-Schrock, O, Patrick, J. A., Blasch, E., 2009. "Video Image Registration Evaluation for a Layered Sensing Environment," *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*.
[46] Blasch, E., Russell, S., G. Seetharaman, G., 2011. "Joint Data Management for MOVINT Data-to-Decision Making," *Int. Conf. on Info Fusion*.
[47] Ling, H., Wu, Y., Blasch, E., Chen, G., Bai, L., 2011. "Evaluation of Visual Tracking in Extremely Low Frame Rate Wide Area Motion Imagery," *Int. Conf. on Info Fusion*.
[48] Blasch, E., Deignan, P. B. Jr, Dockstader, S. L., *et al*., 2011. "Contemporary Concerns in Geographical/Geospatial Information Systems (GIS) Processing," *Proc. IEEE Nat. Aerospace Elec. Conf. (NAECON)*.
[49] Blasch, E., Seetharaman, G. Palaniappan, K., Ling, H., G. Chen, G., 2012. "Wide-Area Motion Imagery (WAMI) Exploitation Tools for Enhanced Situation Awareness," *IEEE Applied Imagery Pattern Recognition Workshop*.
[50] Seetharaman, G., Bao, H., Shivram, G., 1995. "Calibration of Camera Parameters Using Vanishing Points: Stereo Vision Systems," *Journal of Franklin Institute,* Issue: 331-B, Vol. 5, pp. 555-585, September.
[51] Chou, E. C., Iyengar, S. S., Seetharaman, G., Holyer, R., Lybanon, M., 1998. "Velocity Vectors for Features of Sequential Oceanographic Images," *IEEE Trans. on Geo-science And Remote Sensing,* Vol. 36, No. 3, pp. 985-998, May.
[52] Seetharaman, G., 1994. "Image Sequence Analysis: Three Dimensional Perception of Dynamic Scenes," in *Handbook of Computer Vision and Image Processing,* Vol. 2, (Ed.) Tzay Y. Young, Chapter 10, pp. 361-403, Academic Press, San Diego, 1994.
[53] Jhanwar, N., Chaudhuri, S., Seetharaman, G., Zavidovique, B., 2004. "Content Based Image Retrieval Using Motif Co-occurrence Matrix," *Journal of Image and Vision Computing,* Vol. 22, No.14, pp. 1211-1220, Dec.
[54] Seetharaman., G., Le, H., 2006. "Video Assisted GPS for Visual Terrain Navigation using Landmarks," *International Journal of Distributed Sensor Networks,* Vol. 2, No. 2, pp. 103-119.
[55] Liu, Z., Blasch, E., Xue, Z., Langaniere, R., Wu, W., 2012. "Objective Assessment of Multiresolution Image Fusion Algorithms for Context Enhancement in Night Vision: A Comparative Survey," *IEEE Trans. Pattern Analysis and Machine Intel.*, **34**(1):94-109.
[56] Zheng, Y., Dong, W., Blasch, E. 2012. "Qualitative and quantitative comparisons of multispectral night vision colorization techniques," *Optical Engineering*, Vol. 51, Issues 8, Aug.
[57] Blasch, E., Liu, Z., Petkie, D.., Ewing, R., Pomrenke, G., and Reinhardt, K., 2012. "Image Fusion of the Terahertz-Visual NAECON Grand Challenge Data," *IEEE Nat. Aerospace and Elect. Conf (NAECON)*.
[58] Gao, J. Chen, Q. Blasch, E., 2012. "Image denoising in the presence of non-Gaussian power-law noise," *IEEE Nat Aero Conf.*
[59] Blasch, E., Chen, Y., Chen, G., Shen, D., Kohler, R., 2013. "Information Fusion in a Cloud-Enabled Environment," in Choi, B-Y., Han, K., Song, S., (Eds.), *High Performance Semantic Cloud Auditing*, Springer Publishing.