ARL-TN-0891 ● June 2018

US Army Research Laboratory

High-Performance Computing for the Next Generation Combat Vehicle

by Brian J Henz, Leonard Elliot, Michael Barton, and Dale Shires

NOTICES

Disclaimers

ARL-TN-0891 ● June 2018

US Army Research Laboratory

High-Performance Computing for the Next Generation Combat Vehicle

by Brian J Henz and Dale Shires
Computational and Information Sciences Directorate, ARL

Leonard Elliot
US Army Tank Automotive Research, Development and Engineering Center, Warren, MI

Michael Barton
Parsons Corporation, Columbia, MD

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED (From - To)**
June 2018	Technical Note	June 2017–April 2018

4. TITLE AND SUBTITLE	**5a. CONTRACT NUMBER**
High-Performance Computing for the Next Generation Combat Vehicle	
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Brian J Henz, Leonard Elliot, Michael Barton, and Dale Shires	
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
US Army Research Laboratory ATTN: RDRL-CIH-C Aberdeen Proving Ground, MD 21005-5067	ARL-TN-0891
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The development of the US Army Next Generation Combat Vehicle will integrate many innovations in artificial intelligence, autonomy, manned–unmanned teaming, predictive analytics, automatic target recognition, and other functions that require exponential increases in onboard computing capabilities. While the Army will be able to leverage many of the innovations taking place in the commercial sector for driver assist and full autonomous operation, the additional complexities of the battlefield require capabilities not addressed commercially. In this technical note we enumerate challenges faced by the Army and how onboard High-Performance Computing is critical to addressing the challenges.

15. SUBJECT TERMS

Next Generation Combat Vehicle (NGCV), mobile computing, High-Performance Computing, artificial intelligence (AI), Human–Agent Teaming

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
					Brian J Henz
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER (Include area code)**
Unclassified	Unclassified	Unclassified	UU	19	410-278-6531

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures **iv**

1. Introduction **1**

2. Next Generation Combat Vehicle Computational Requirements **1**

2.1 Unrestricted Maneuverability 2

2.2 Perception with Deception 2

2.3 Damage Adaptation 2

2.4 Active Protection System 3

2.5 Embedded Training 3

3. Computational Technology **4**

3.1 Embedded Automotive Electronics 4

3.2 Edge Computing 4

3.3 Machine Learning 5

3.4 Communications and Electronic Warfare 6

3.5 Cyber Issues 6

3.6 Software Development and Sustainment 6

4. Integration Strategy **7**

5. Modeling and Simulation **8**

6. Conclusions and Way Forward **9**

7. References **11**

List of Symbols, Abbreviations, and Acronyms **12**

Distribution List **13**

List of Figures

Fig. 1 Mobile HPC will provide resources to generate a synthetic environment, drive displays, and provide synthetic sensor data for embedded training.......... 3

Fig. 2 Networking diagram for mobile HPC on NGCV including autonomy sensors, situational awareness sensing, CANBUS (Controller Area Network bus), and high-speed interconnect.......... 10

1. Introduction

The development of the Next Generation Combat Vehicle (NGCV) will require technological advancements in many areas, including lethality, protection, autonomy, human–agent teaming, and electromagnetic capabilities. What ties all of these future capabilities together is the requirement of vast computational resources to support the artificial intelligence (AI) implicit in bringing these advancements to the battlefield. The operating environment of the NGCV will be such that communications will be severely limited, if available at all, systems will be under constant cyber-attack from a near peer adversary, and adversarial AI may be actively attempting to deceive all sensors—all occurring under severe size, weight, power, and time available constraints. These factors, and more, are the motivation for developing this strategy of mobile High-Performance Computing (HPC)* for the NGCV.

2. Next Generation Combat Vehicle Computational Requirements

Future military vehicles will require capabilities beyond autonomous maneuverability, including intelligence analytics and situational understanding, to achieve autonomous operation. Military vehicles must maneuver over and around obstructions, predict and react to various soil conditions, and operate with and adapt to damage, well beyond the demands of commercial vehicles. Situational understanding requires perception and reasoning under uncertainty, cooperation with other agents, and reasoning about adversarial intent, all requiring complex computations in a dynamic environment where communications are severely limited or unavailable. We discuss each of these challenges in detail. A final consideration is that with ever-increasing computational and communications resources placed on vehicles, there is attendant heat generation/rejection and radio frequency (RF) emission. Signature management, at least for infrared and RF, needs to be a consideration from the outset, rather than an issue to be resolved after the fact.

While commercial vehicles maneuver under constraints of predetermined roads of varying quality and vastly differing environmental conditions (e.g., rain, snow, ice, fog, smoke), combat vehicles face the additional complexity and uncertainty of maneuvering over a multitude of soil conditions, vegetation, dynamic environments, and under active deception. One solution to begin addressing these

* High-Performance Computing is used here as a relative term to denote an order of magnitude or more increase over computing resources available on future contemporary commercial vehicles.

challenges is to develop and execute onboard computational models of soil, roads, and vegetation to predict in near-real-time uncertainty and provide tactically sensible courses of action to the Soldier or an autonomous agent. Such computations require general purpose calculations that can vary significantly in complexity from model to model.

2.1 Unrestricted Maneuverability

Path planning (and dynamic replanning) in an unrestricted environment is an NP-hard computational problem, meaning that large numbers of possible routes must be evaluated, even with heuristic methods to limit the number of evaluations. The Army problem adds complexity by operating in a complex, dynamic environment that is constantly changing, with fewer constraints on mobility for evaluating goals and utility. Modeling of the physical environment to include obstructions, terrain, adversary's intent, and so on, is required to plan routes that will increase the chance of success while providing an operator with possible courses of action.

2.2 Perception with Deception

Maneuverability on the battlefield has many distinct challenges not seen in the commercial vehicle space, including the potential for malicious concealment and deception by adversaries. Tactical autonomous vehicles must navigate rapidly changing landscapes by learning to recognize concealed, camouflaged, and deceptive obstacles, behaviors, and threats. Military vehicles' onboard computing will require accurate perception and real-time understanding in a contested and deceptive environment, enabled by robust machine learning algorithms. The path to the NGCV will likely see a proliferation of onboard sensors that generate data that must be processed at the point of need. Examples of these include ultra-wideband radar that can scan below the surface of the soil for buried objects, spectrum analyzers searching for adversarial activity, multimodal communications that must be intelligently managed, and acoustic sensors that can detect movement at great distances.

2.3 Damage Adaptation

Autonomous vehicles that adapt to and function with damage are critical to robust manned–unmanned teaming (MUM-T) and autonomous vehicles (Cully et al. 2015). The US Army Research Laboratory (ARL) recognizes the importance of imbuing teams of heterogeneous robots and sensors with the intelligence to learn and adapt to different settings and perform new tasks along with humans and has initiated this as a core research aspect of the FY18 Distributed and Collaborative

Intelligent Systems and Technology Collaborative Research Alliance. To achieve the goal of adaptive and resilient teams of robots and humans, significant computing resources must be available onboard the autonomous systems or reachable within a contested and congested environment. The computing resources will support the fusing of sensor data, damage detection and failure prediction/inference, and eventual modifying of operating variables (speed, direction, etc.) to reduce the use of damaged/failing parts.

2.4 Active Protection System

Current active protection systems rely on self-contained sensing, processing, and response initiation due to the very limited time available to sense a launch, predict impact location, and initiate active response from the system. Even so, much information can be extracted from this system to provide situational awareness of opposing force locations, maneuver, and intent. Processing and understanding of the information on board and within the local MUM-T will be necessary for cooperative responses and maneuvers. Future active protection systems are even envisioned to provide cooperative defense inter-vehicle, which will be highly dependent upon decreasing the time to decision within a distributed processing and communications environment.

2.5 Embedded Training

Training within the vehicle through the use of mobile HPC capabilities will provide an embedded training environment wherever the vehicle is deployed. These training capabilities require the ability to generate synthetic sensor data and drive displays in real time (i.e., emulation with hardware and human-in-the-loop). An example of the screens available in future combat vehicles is seen in Fig. 1, alongside computer-generated optical and lidar data from the Autonomous Navigation Virtual Environment Laboratory (ANVEL).

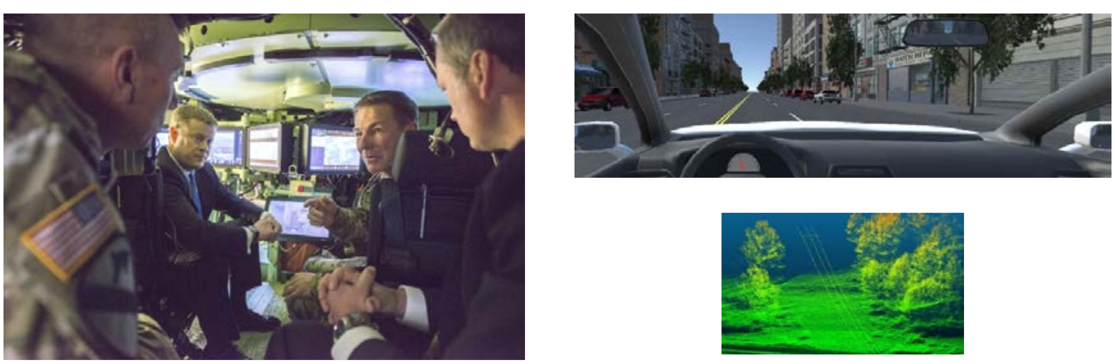

Fig. 1 Mobile HPC will provide resources to generate a synthetic environment, drive displays, and provide synthetic sensor data for embedded training

3. Computational Technology

3.1 Embedded Automotive Electronics

The automotive industry is moving ahead rapidly with increasing the number and capabilities of integrated circuits (ICs) on vehicles. The growth rate of the automotive IC market is projected to be 10.3%, while the growth rate of the IC market for personal computers, set-top boxes, touchscreen tablets, and video game consoles is expected to be negative (IC Insights 2016). The automotive growth is driven by systems that provide partial or high automation and that may eventually lead to fully autonomous vehicles; it is boosting total IC content per automobile. The computational load of next generation advanced driver assistance systems jumps very quickly with every attempt to widen the sensing range, boost detection precision, and execute more powerful algorithms to respond quickly and effectively to a broad spectrum of driving conditions (IC Insights 2016). The market share of the automotive IC vendors is given in McGrath (2017). Not on this list are rapidly growing investments by vendors from other parts of the IC marketplace developing automotive solutions, such as Intel, NVidia, AMD, and ARM.

The data in McGrath (2017), along with developments from major manufacturers such as Intel, NVidia, AMD, and ARM, represent a baseline of commercially available processing. Ongoing relationships with the chip developers will give us insight into their directions and how that intersects with Army requirements. Such analyses could conceivably identify limitations of onboard future capabilities or inform Army investments in custom processor design, especially for co-design of software and processors for military-specific applications.

3.2 Edge Computing

While commercial communications benefit from robust infrastructure, with highly engineered cellular network providers interconnected with very high bandwidth backhaul links, military operations typically must bring their own communications capability. The military's mobile devices have very limited access to cloud-based computational capability on the battlefield. Therefore, tactical units must deploy localized edge processing that does not rely heavily upon communications infrastructure. HPC at the tactical edge provides the computational capability at the source of tactical data, the sensors, and users on the battlefield. This array of networked entities constitutes a tactical Internet of things, termed the Internet of Battlefield Things. Power-efficient edge computing (Satyanarayanan et al. 2013, 2017a, 2017b) enables the use of machine learning algorithms locally, integrated with programmable network controllers to intelligently push data over disconnected, intermittent, low-bandwidth networks while minimizing the RF emissions.

Edge computing is enabled through cloudlets, also referred to as micro-clouds, and are localized trusted, resource-rich computers or a cluster of computers, well-connected to the tactical Internet within one wireless hop; proximity is the key. Cloudlets, just as clouds, are enabled by virtualization. Clouds virtualize an entire computer system using virtual machines, requiring substantial resources. Cloudlets demand a lighter-weight solution, and one option is containers. Instead of virtualizing an entire computer, containers virtualize only the operating system and take advantage of the host computer, such as the Linux kernel, network, and various services. Containers can be tailored to single solutions, such as a machine learning container and a video processing container.

3.3 Machine Learning

Many of the capabilities just described depend on the development, training, and sustainment of machine learning tools. Current machine learning models (LeCun et al. 2015) are limited in their applicability due to the requirement for very large curated training data sets and poor accuracy with noisy samples. Larger data sets and models lead to better accuracy; however, the amount of computation time also increases. Situational understanding during combat requires continuous learning of new patterns in the presence of adversarial deception. Use of machine learning in highly varying environments requires extremely high computational power, such as general purpose graphics processing units (GPUs). The application of such perception and intelligence systems in real time is limited by how quickly the system can classify a set of sensor inputs.

Tactical applications of machine learning must perform within the constraints of sparse, uncertain, dynamic data. Applications cannot wait on new algorithms to be trained in garrison and forwarded to the operational environment; in theater, data must be applied to retrain existing algorithms. The current workhorse for training machine learning algorithms is the GPU. Inferencing—the use of the trained tool—may depend on a completely different platform. And power use is always a concern. Neuromorphic computing may offer a solution to the training/retraining, inferencing, and power issues. The neuromorphic processor is an example of brain-inspired computing. Neuromorphic processors exhibit substantially lower power requirements—as much as 1000 times—than their x86 and other von Neumann architecture counterparts. They have demonstrated value in classification applications or, more generally, in dynamic learning in the context of complex and unstructured data (Schuller and Stevens 2015). Like any other software-intensive system, sustaining machine learning systems must be planned for ab initio (Sculley et al. 2015).

3.4 Communications and Electronic Warfare

Current tactical radios and electronic warfare systems are packaged as separate point-solutions requiring their own packaging, cooling, processing elements, and antennas. Emerging initiatives such as the Communications-Electronics Research, Development and Engineering Center's Modular Open Radio Architecture seek to establish a common communication infrastructure and processing architecture to consolidate and develop these functions. A significant tactical overmatch may be achieved by fully analyzing EM spectral information and combining it with coordinated software-defined radio communications; however, these applications require tremendous amounts of computational power to process the EM signals and execute the associated algorithms. Capabilities such as jamming, direction-finding, spoofing, and stealth communications can all be enhanced and made more efficient with HPC technologies; these may prove to be crucial advantages in future conflicts.

3.5 Cyber Issues

Increased reliance upon software-intensive designs and networked communications increases cyber vulnerabilities in addition to electromagnetic warfare threats. To date, we have managed with added-on and built-in protection but must now *design-in* cyber protection. This requires cyber testing over the systems' lifecycle, including vulnerabilities created from integrating multiple disparate systems. The National Defense Authorization Act of 2016 created a statutory requirement for joint cyber testing (Hinton et al. 2017). In-lab testing of cyber and electronic warfare vulnerabilities through emulation with hardware-in-the-loop (HWIL) is a proven method for evaluation and analysis of integrated systems as part of an LVC (Live/Virtual/Constructive) strategy. HPC on the vehicle will support in-situ emulation, advanced intrusion detection systems (Stojmenovic 2014), anomaly detection, and machine learning methods to rapidly identify unexpected behaviors.

3.6 Software Development and Sustainment

An issue confronting the Department of Defense (DOD) for years has been the timely and affordable development and sustainment of low-defect, low-vulnerability software. Many software development paradigms have been used but not with great success for DOD systems. We constantly field defective software and then spend large sums of money patching them. While algorithms are critical to machine learning, it is their software implementations that deliver the promised capabilities. A critical property of software implementations is that to remain useful, they must evolve during development and operation to accommodate changing understanding, needs, infrastructure, and technology. It is well known that efforts to develop and sustain software implementations on time and on schedule produce buggy, vulnerable software. Neither better management nor agile development methods are sufficient to address weaknesses inherent in the existing hand-coding software development and sustainment paradigm. Addressing this challenge requires science and technology investment in alternative software development and sustainment paradigms. This applies across the board to future systems, such as NGCV, autonomous systems, cyber security, networks and communications systems, and sensor systems (Ardis et al. 2000).

4. Integration Strategy

The ultimate purchaser of this NGCV will be a program manager (PM). As we learned from the Future Combat Systems (FCS) program, the PM must be very careful of external programs and capabilities that must be integrated into his/her system. For example, the Joint Tactical Radio System (JTRS) and Warfighter Information Network – Tactical (WIN-T) were programs of record that were included as part of FCS systems, yet the FCS developer did not have the requirement to integrate the systems and was not resourced to do so; and neither were the JTRS and WIN-T PMs resourced to integrate their systems into FCS. Related to this issue is that often integrated systems are designed to have a greater capability than each individual constituent, but that capability is realized from the interaction among the constituents. For this to be realized, someone has to be in charge of the integration function and testing of the interfaces and integrated system. In addition, capabilities may arise from computations among the constituents; one PM must be in charge and resourced to design, develop, and test the integrated computational capability and ensure that each constituent is a balanced element of the whole and that communications bottlenecks, computational latency, interference, and other impediments do not exist and are not introduced as part of the integration process.

Integration issues are first discovered in testing, when everything is pulled together to ascertain if the system was built correctly (developmental testing) and if the right system was built for the Soldiers' needs (operational testing). With the increasing complexity of technology, systems, and integration, the test community needs to be included in design and development phases, even at the conceptual stage, to understand what they may have to test and to reconcile that with instrumentation, facilities, skills, computation, and other requirements. Experience from the testers can be useful to inform early decisions about manufacturing, testability, and sustainment of a system, and issues that have been discovered in related systems. Finally, the test community maintains a comprehensive database of Army (and Marine) vehicles, and ARL and the US Army Test and Evaluation Command (ATEC) are developing HPC-based tools to exploit this historical database for design, analysis, and forensics of ground vehicles.

It is likely that we are currently coming to the end of an era (Moore's law) where the performance gains in general purpose computing are available by simply decreasing the feature size of devices. During the Moore's law era, there was limited return on investment for the development and production application of specific devices because of the economics of scale. Evidence of this is seen in industry titans investing in the development of low precision, and thus energy efficient, architectures for machine learning based upon using deep neural networks. Increases in performance of general purpose processors from Intel and AMD initially switched from monolithic cores with increasing clock speeds to multi- and eventually many-core architectures with 16+ general purpose cores per processor. With increasing complexity of further feature size beyond a commonly assumed limit of 5 nm, because of physical constraints, we are likely to see a proliferation of application-specific processors with eventual commoditization of manufacture using open-source architecture designs. This is analogous to the switch from commercial software applications to open-source development and new business models. This transition will put the onus on experts in hardware/software co-design to provide optimization of computational resources for the NGCV.

5. Modeling and Simulation

Modeling and simulation are essential for vehicle development, analysis, and testing, and for integration of the vehicle and its systems with external systems. Vehicle models, sensor models, network and communications models, and mobility models are required for creating a complete virtual representation of the NGCV and how it will interact with other systems and with its environment.

Computational tools are used throughout the acquisition process from the earliest research and analysis of alternatives to detailed trade studies for final design. The goal is to develop codes that are multi-fidelity and scalable, taking advantage of current heterogeneous clusters, computational mathematics, and software development practices. This allows the same code to be used low fidelity for preliminary design and real-time HWIL, or high fidelity for research, final design, and all digital simulations. The same geometric database, grid generation, environmental inputs, and visualization tool are used throughout, and verification and validation is performed once and maintained with the code throughout its life and that of the system being developed. Multi-fidelity—the ability to trade accuracy for speed—is meant in two ways. The first applies to lowering fidelity for executing thousands of simulations in early concept development versus executing detailed analyses in final design; the second applies to signature calculation for real-time versus non-real-time scene generation. Currently, there is no single computational mechanics code that can trade simulation accuracy for speed to address vehicle development needs across the entire acquisition problem space. Quantifying the error is absolutely critical in the verification, validation, and uncertainty quantification process.

6. Conclusions and Way Forward

Integrating all of the future capabilities and intelligence for the NGCV will require a strategy for mobile HPC. Additionally, the challenges and solution look different than the solution for commercial vehicles. The computer architectures will need to support autonomous or assisted mobility, much like commercial vehicles, but additional functionality, such as unrestricted mobility, cyber analysis, and course of action analysis, will require a recipe of heterogeneous open-source and commercial off-the-shelf devices. The future becomes less certain as we move further out, and more functionality must be included in the vehicle to support fully autonomous maneuver in a multidomain battlespace. It is under this uncertainty that this strategy is being developed, refined, and iterated upon, including inserting new technologies as they emerge. Evaluating new hardware configurations will necessitate the use of an HWIL testbed for accelerated evaluation and transition of research innovations, technology exchange and transition, and sharing of lessons learned. Transition of this computing strategy and AI algorithms and software will be enabled through the use of this testbed from ARL and to the US Army Tank Automotive Research, Development and Engineering Center. Prototype builds and field testing will occur at ATEC, with ARL working collaboratively at each step to continue innovating and keep feeding new capabilities into the development process. Figure 2 illustrates this vision and connectivity for mobile HPC that is general purpose and able to interact and integrate with dedicated computing resources from multiple sources and vendors.

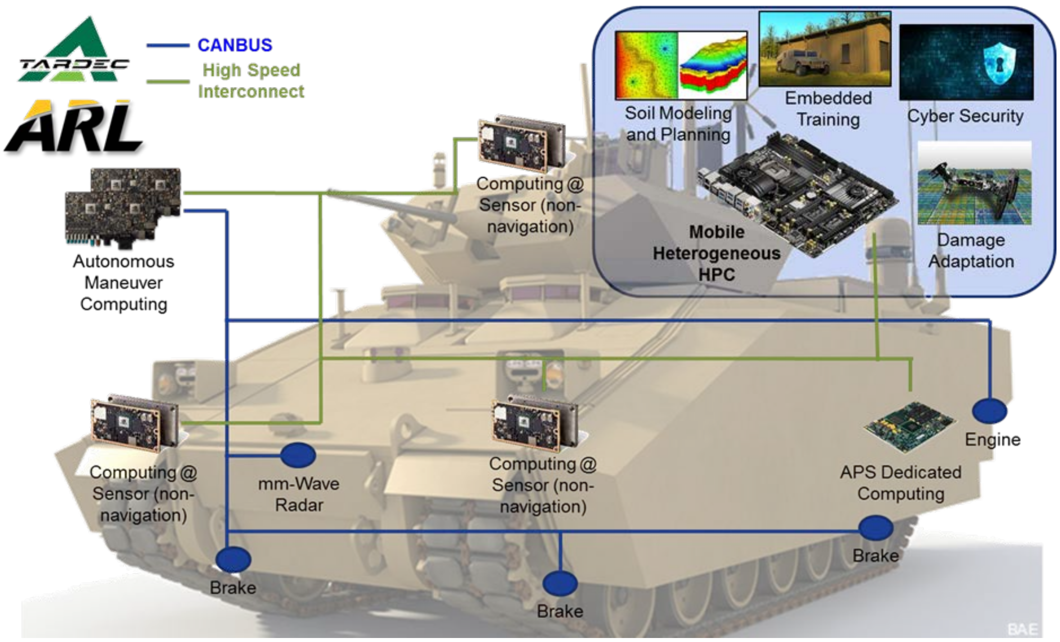

Fig. 2 Networking diagram for mobile HPC on NGCV including autonomy sensors, situational awareness sensing, CANBUS (Controller Area Network bus), and high-speed interconnect

Achieving this vision of advanced AI on the NGCV will require a risk reduction effort that rapidly provides evaluations of technologies and capabilities for transition from basic and applied research to prototypes and live demonstrations. Evaluation of algorithms, software, and hardware capabilities will require hardware and human-in-the-loop testbed capabilities to create a synthetic environment for sensor data, vehicle physics, and so on. To continue advancing this vision, it is recommended that the Army develop a testbed environment based on ANVEL and the Virtual Autonomous Navigation Environment (Rhode 2009).

7. References

Ardis M, Daley N, Hoffman D, Siy H, Weiss D. Software product lines: a case study. Software: Practice and Experience. 2000;30:825–847.

Cully A, Clune J, Tarapore D, Mouret J-B. Robots that can adapt like animals. Nature. 2015;521(7553):503–507.

Hinton GD, De Le Cruz D, Smith K. Test resource management center: statutory and regulatory missions. The ITEA Journal. 2017;38(2):102–107.

IC Insights. Automotive IC market to display strongest growth through 2019; 2016 Apr 21 [accessed 2018 Apr 23]. http://anysilicon.com/automotive-ic-market/.

LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521:436–444.

McGrath D. Automotive IC vendor ranking stays largely unchanged. Np: EE Times; 2017 Mar 28 [accessed 2018 June 20]. https://www.eetimes.com/document.asp?doc_id=1331530.

Rhode M. An interactive physics-based unmanned ground vehicle simulator leveraging open source gaming technology: progress in the development and application of the virtual autonomous navigation environment (VANE) desktop. SPIE; 2009; Orlando, FL; p. 73321C.

Satyanarayanan M. Edge computing for situational awareness. IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN 2017); 2017a Jun 12–14; Osaka, Japan.

Satyanarayanan M. The emergence of edge computing. Computer. 2017b;50(1):30–39.

Satyanarayanan M, Lewis G, Morris E, Simanta S, Boleng J, Ha K. The role of cloudlets in hostile environments. IEEE Pervasive Computing. 2013;40–49.

Schuller IK, Stevens R. Neuromorphic computing: from materials to systems architecture. US DOE Report of a Roundtable Convened to Consider Neuromorphic Computing Basic Research Needs; 2015 Oct 29–30.

Sculley D, et al. Hidden technical debt in machine learning systems. NIPS 2015; 2015 Dec 7–12; Montreal, Canada.

Stojmenovic I. The fog computing paradigm: scenarios and security issues. Federated Conference on Computer Science and Information Systems; 2014; Warsaw, Poland. Piscataway (NJ): Institute of Electrical and Electronics Engineers (IEEE); p. 1–8.

List of Symbols, Abbreviations, and Acronyms

AI	artificial intelligence
ANVEL	Autonomous Navigation Virtual Environment Laboratory
ARL	US Army Research Laboratory
ATEC	US Army Test and Evaluation Command
CANBUS	Controller Area Network Bus
DOD	Department of Defense
EM	electromagnetic
FCS	Future Combat Systems
GPU	graphics processing unit
HPC	High-Performance Computing
HWIL	hardware-in-the-loop
IC	integrated circuit
JTRS	Joint Tactical Radio System
LVC	Live/Virtual/Constructive
MUM-T	manned–unmanned teaming
NGCV	Next Generation Combat Vehicle
NP	nondeterministic polynomial-time hardness
PM	program manager
RF	radio frequency
WIN-T	Warfighter Information Network – Tactical

1 (PDF)	DEFENSE TECHNICAL INFORMATION CTR DTIC OCA
2 (PDF)	DIR ARL IMAL HRA RECORDS MGMT RDRL DCL TECH LIB
1 (PDF)	GOVT PRINTG OFC A MALHOTRA
1 (PDF)	ARL RDRL CIH C B HENZ