

86th IFIP 10.4 Meeting – Gold Coast, Australia

Session 1 summary

Presented by Ilir Gashi

Overview

- Title of session: Security, Safety and Fault Tolerance of Al systems
- Two talks:
- On Fault Tolerance of Al Systems
 - Long Wang, Tsinghua University, China
- Safe and Secure AI/ML-driven Autonomous Vehicles? Not anywhere near yet ...
 - Paulo Esteves-Veríssimo, RC3 (Resilient Computing and Cybersecurity Centre), CEMSE, KAUST, Saudi Arabia



On Fault Tolerance of AI Systems

- The outline of the talk from Long
 - Fault Tolerance (FT) in Classical Computing
 - > FT of AI Systems
 - FT of Al Applications
 - FT of Al-Hosting Systems
 - Case Study: FT of AIGC Applications

Al Applications/
Services

Al-Hosting System/Platform

Al Systems

- The main aim of the talk was to compare the fault tolerance strategies, fault and failure models for classical computing systems with those of AI applications and AI hosting systems
- The focus of Long's talk was on fault tolerance against non-maliciously induced faults and failures







Overview of Classical Reliable Computing

Reliable/Dependable Computing **Basic Concepts Technology** Validation Analytic Model **Impairments Properties** Fault Metrics ault Fault Fault Fault Prevention Removal Forecast Tolerance Injection Failure Rate Reliability Fault Fault Error Detectio Recovery Rate Location Error Recovery **Formal** Availability Mean Time To Error (checkpoint. Method Failure (MTTF) Problem rollback,replica ...) Failure Fault Serviceability Diagnosis Mean Time To Recovery **Fault** Mask ng (MTTR) Dependability Simulation (ECC, Error Containment Mean Time Between Hamming, Field Data Failures (MTBF) High Availabil ty (HA ...) Study Reliability Function

Disaster Recovery

Long Wang Availability Function



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Fault Tolerance in Classical Computing (cont.)

- Error Detection
 - Watchdog timers, Heartbeats
 - Consistency and capability checking
 - Exception handling
 - Control-flow checking
 - Data audits, data flow checking
- Error recovery
 - Restart
 - Checkpoint and rollback
 - Rollforward
 - Replicas/replication with failover support

- Fault tolerance
 - Hardware Redundancy
 - Triple Module Redundancy, m-out-of-n structure, active-active, active-passive
 - Voting
 - Software Fault Tolerance
 - Robust data structures
 - Recovery blocks
 - N-version programming
 - Process pair
 - Voting or Acceptance Test
 - Combining specific error detection and error recovery techniques

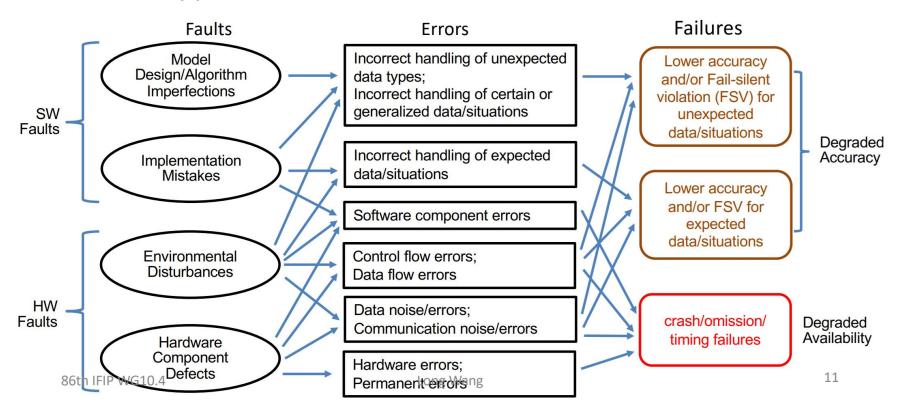
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FT of AI Applications – Fault Model and Error Manifestation









Fault Tolerance of AI Applications

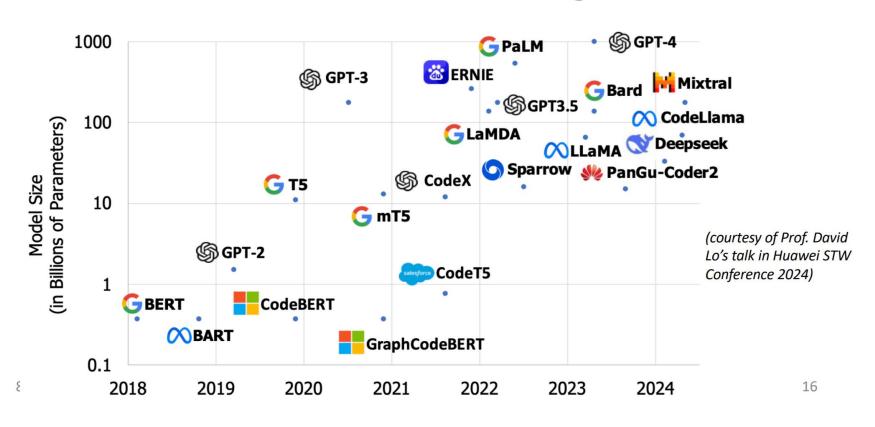
Failure Category	Degraded Accuracy for Inference Tasks	Degraded Accuracy for Training Tasks	Degraded Availability
Error/Failure	Incorrect task results (e.g. misclassification)	Incorrect model states (e.g. bad model weights) Longer convergence	 Crash, omission, timing failures Control flow errors Data flow errors
Error Detection	 The failure (incorrect result) itself E.g. user feedback Acceptance check Rule based Al model based Accuracy metric monitoring 	 Incorrect inference results on test data sets during training Lower accuracy Range checking of model weights or intermediate values Task-specific metrics for detection 	Classical error detection Crash/hang detection, heartbeat, consistency checking, multi-replica vote, control/data flow check, data audits
Error Recovery/ Tolerance	 Re-execute, restart Rollforward Multi-replica vote (e.g. TMR) May be in partitioned module level Multi-version or diversified models Error analysis and root-causing Improving with fine-tuning Re-training 	Checkpoint/backup and rollback Saving model state periodically for recovery without losing progress Multi-replica vote TMR-like Ensemble Learning May be in partitioned module level Error analysis and root-causing Improving with fine-tuning	For training tasks Checkpoint and rollback, multi-replica vote For inference tasks Re-execute, restart, rollforward, multi-replica vote, replicas/replication with failover







LLM Models Grow to Huge Sizes

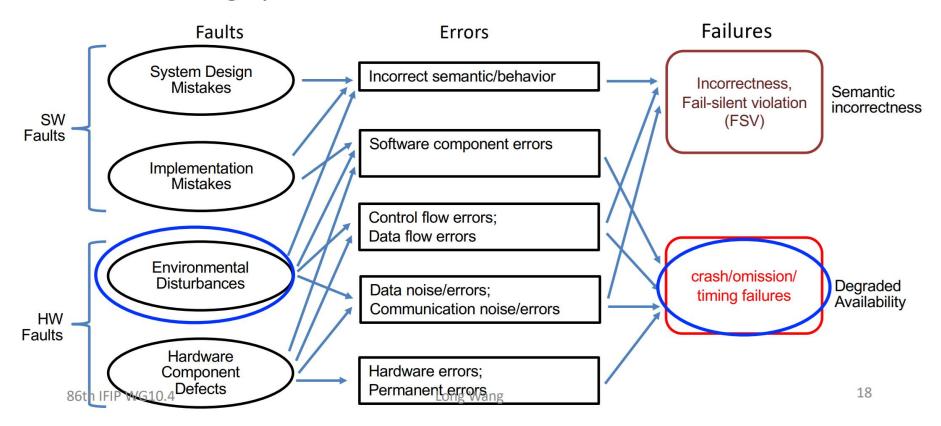








FT of AI-Hosting Systems – Fault Model and Error Manifestation









Fault Tolerance of Al-Hosting Systems

- Failure Category
 - Degraded availability
 - Semantic incorrectness
- Error Detection
 - For degraded availability
 - Classical error detection (process crash, system exception, log information, error-detecting code like CRC checksum)
 - For semantic incorrectness that result in degraded accuracy, and for other semantic incorrectness
 - · Error detection of AI application outputs against degraded accuracy
 - May need specific error detections (error-detecting code like CRC checksum, rule check, control/data flow check, customized check)
- Error Recovery and Tolerance
 - Similar to error recovery and tolerance of cloud systems or data centers
 - E.g. fail-forward for inference jobs, checkpoint/rollback for training jobs
 - As AI-Hosting systems are just such infrastructure as cloud systems, data centers, or simpler-structure computer systems

CITY

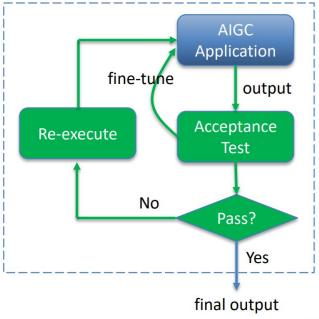




Case Study: FT of AIGC Application using Acceptance Test

- Combining error detection and error recovery for providing FT of AI applications
 - AIGC application: Al-generated content
 - Error detection: acceptance test
 - Error recovery: re-execute
- Acceptance Test
 - Rule based
 - Depending on scenarios, there may be rules that can be implemented to check if the output of is correct
 - AI model based
 - Al models as discriminators to check if the output is acceptable or not
- If the acceptance test fails, re-execute the AIGC application with different initial input
- The final output has much higher accuracy than the original one
- The acceptance test can also help fine-tune the AIGC application/model

Fault-Tolerant AI Application



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Summary

- FT technologies in classical computing mostly still applies to AI applications/ systems (with adaptations if needed)
 - Error detection, error recovery, and a combination of them
 - E.g. acceptance test largely improves the AI application accuracy
- Failure models of AI applications/systems mainly fall into two categories
 - Degraded accuracy and degraded availability
- Semantic analysis based rule checking helps detect degraded accuracy of AI applications
- We can learn a lot from experiences of FT in cloud and supercomputer systems for FT of AI applications/systems, because
 - All applications share a lot of similarities with supercomputing applications or cloud services
 - Al-hosting systems share a lot of similarities with cloud systems and supercomputer systems

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Q&A on Long's talk

- Good Q&A on the talk from Long
- Colleagues encouraged Long to expand the analysis to look at not only non-malicious but malicious faults and failure also.
- The Fault-Error-Failure (FEF) model can still be used, and the extension done in the MAFTIA project for example can be applied (the Attack-Vulnerability-Intrusion Fault-Error-Failure model):
 - D21.pdf (ncl.ac.uk)

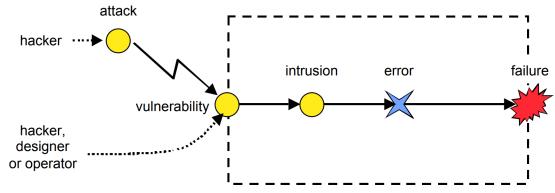


Figure 8 — Intrusion as a composite fault



Safe and Secure Al/ML-driven Autonomous Vehicles? Not anywhere near yet ...



Resilient Computing and Cybersecurity Center



Brief Analysis of the Cyberspace today

- distributed infrastructure:
 - Pervasive CPS and IoT; seamless integration with Internet/Cloud/Web.
- highly exposed to threats:
 - Huge *pressure to go "digital"*: Govs; BigTechs; Social nets.
- steadily increasing software vulnerabilities:
 - Common SW yearly *rate increased* 2-3-fold; *CPS/loT* in great increase
- degradation of the threat surface:
 - Even more powerful adversary actors and sophisticated exploit tools



So, what's wrong about the current autonomous vehicles ecosystem?

- To start with, the very notion that there is an ecosystem is inexistent
- An analysis of the ecosystem as a critical infrastructure is missing





Safety-security gap in vehicle ecosystems

حامعة الملك عبدالله للعلوم والتقنية King Abdullah University of Science and Technology

Faults in a well designed car ecosystem lead to an infinitesimal and acceptable probability of catastrophic failure;

Faults in a well designed car may imply a nonnegligible probability of catastrophic failure

Vulnerabilities in a car ecosystem will lead, rather sooner than later, to catastrophic failures;



Towards Safe and Secure Autonomous and Cooperative Vehicle Ecosystems. Lima, A; Rocha, F; Volp, M; Verissimo, P. in Proc's 2nd ACM Workshop on Cyber-Physical Systems Security and Privacy (2016, October) @CCS, Vienna-Austria





Autonomous Vehicle Ecosystem



Towards Safe and Secure Autonomous and Cooperative Vehicle Ecosystems. Lima, A; Rocha, F; Volp, M; Verissimo, P. in Proc's 2nd ACM Workshop on Cyber-Physical Systems Security and Privacy (2016, October) @CCS, Vienna-Austria

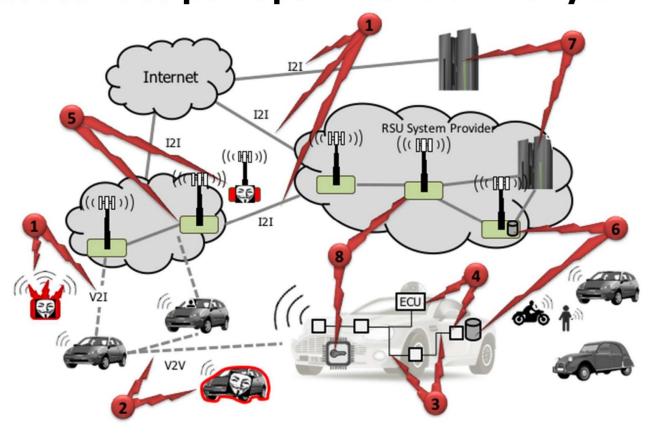


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Autonomous vehicle ecosystem العلوم والتقنية King Abdullah University of threat surface perhaps wider than many think cience and Technology



Threat Vectors



«IF IT AIN'T SECURE, IT AIN'T SAFE»

How serious is that?



Safety-security gap in vehicle ecosystems

Faults in a well designed car ecosystem lead to an infinitesimal and acceptable probability of catastrophic failure;

Faults in a well designed car may imply a **non-negligible** probability of catastrophic failure

Vulnerabilities in a car ecosystem **will** lead, rather sooner than later, to catastrophic failures;



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Homogeneous ML-based systems cannot give strong assurance and resilience guarantees



Status-quo

 Autonomous cars use ML-powered multi-sensor perception (mainly vision) and control, and sometimes redundant modules to which the MLearned module hands over in case of problems.

Assurance

 LOW- Infeasible to provide reliable figures/conclusions, impossible to certify

Resilience

 LOW- Fair success in handling unforeseen, emergent or out-ofenvelope behaviours; often even blind to those situations



Philosophical side of the problem:

«Control the physics of event interleaving in autonomous object ecosystems, acting in real time, in open and largely unpredictable environments»



A part of the long journey towards



RESILIENT AUTONOMOUS VEHICLE ECOSYSTEMS

More recently, A. Shoker and R. Yasmin at CybeResil@KAUST, M.Voelp CRITIX@UNILU, V. Rahli @U.BIRMINGHAM, J. Decouchant@U.DELFT







Project Info

[2001-04]

INFORMATION SOCIETY TECHNOLOGIES (IST) PROGRAMME



Project acronym: *CORTEX*Project full title:

CO-operating Real-time senTient objects: architecture and EXperimental evaluation

• Members:

- Univ. Lisboa Fac. Of Sciences (PT) (proj. coord.)
- Trinity College of Dublin (IR)
- U. of Lancaster (UK)
- U. of Ulm (DE)

• Duration:

- 3 years, starting April 2001
- Budget:
 - 2 MEURO





Sentient objects' interaction model

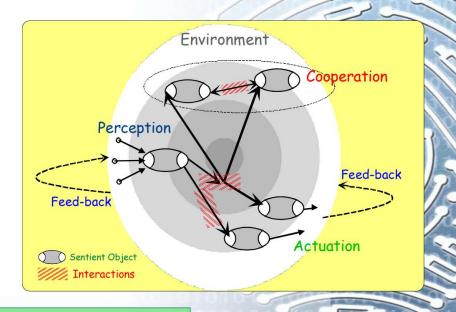


Abstract safe distributed real-time (DRT) autonomous control of free-running objects

should support the classes of R/T interactions objects need to perform:

- sentience of body and of environment;
- environment-to-object and vice-versa;
- object-to-object





[P. Veríssimo and A. Casimiro. The Timely Computing Base Model and Architecture. IEEE Tacs. on Computers, 2002]



KARYON PROJECT: Kernel-Based ARchitecture for safetY-critical cONtrol

2011-2014



Academia & Research Institutes SMEs and Industry

Proof-of-concept prototypes Simulations







EMBRAER



UAS/Aircraft flight mission



CHALMERS







Automotive

Adaptive cruise control Coordinated lane change Coordinated intersection crossing

Provide system solutions for predictable and safe coordination of smart vehicles that autonomously cooperate and interact in an open and inherently uncertain environment



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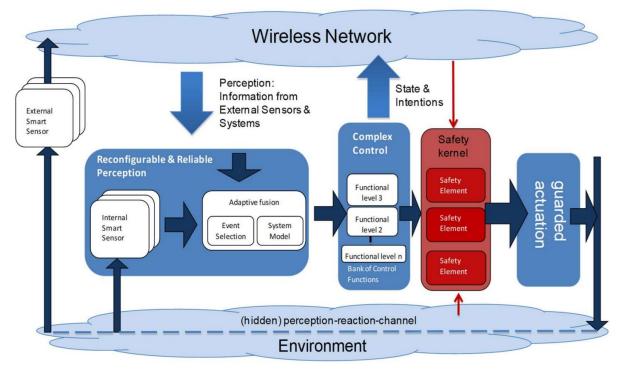






KARYON architectural view: proof of concept of hybridisation for safety







A. Casimiro, J. Kaiser, E. Schiller, P. Costa, J. Parizi, R. Johansson, R. Librino, "The KARYON Project: Predictable and Safe Coordination in Cooperative Vehicular Systems", in 2nd Workshop on Open Resilient Human-aware CPS (WORCS'13), Jun. 2013.



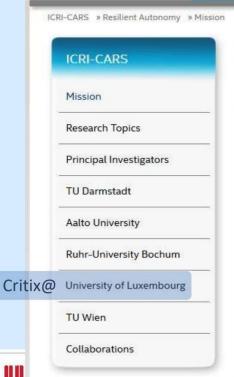
Intel Collaborative Research Institute for

Collaborative Autonomous & Resilient Systems (CARS)

securityandtrust.lu

2017-2020

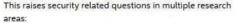
https://www.icri-cars.org/



Intel Collaborative Research Institute for Collaborative Autonomous & Resilient Systems (ICRI-CARS)

About Collaborative Autonomous and Resilient Systems (CARS)

The mission of the ICRI-CARS is the study of security, privacy, and safety of autonomous systems that may collaborate with each other. Examples include drones, self-driving vehicles, or collaborative systems in industrial automation. CARS introduce a new paradigm to computing that is different from conventional systems in a very important way: they must learn, adapt, and evolve with minimal or no supervision. A fundamental question therefore, is what rules and principles should guide the evolution of CARS?



- 1. Trustworthy and Controllable Autonomy
- 2. Fair and Safe Collaboration Tolerating Failures and Attacks
- 3. Intelligent Security Strategies for Self-Defense and Self-Repair
- 4. Integration of Safety, Security, and Real-time Guarantees
- 5. Autonomous Systems, Ecosystem Scenarios, Requirements, Case Studies, and Validation
- 6. Advanced Platform Security for Long-term Autonomy



UNIVE



Resilience enablers for autonomous and collaborative vehicles



Applied safe and secure DRT autonomous control --- general driving

- Powerful architectures (e.g. manycores), capable of: highpower computing, enabling security/safety defenses
- Secure and dependable real-time communication, V2V and V2I, despite accidents and attacks
- Automatic in-car resilience mechanisms for safety and security (gateway, ECU, trusted components/enclaves)

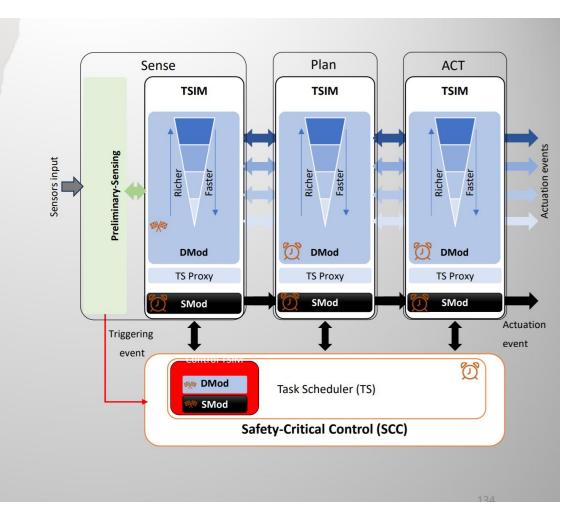


Intrusion Resilience System (IRS) KAUST Trustworthy Autonomous In-house Vehicles Architecture (SAVVY) **Projects** 2021----Towards sustainable security and safety In AV control



Savvy Architecture

- Preliminary Sensing
 - o Detect an Event
 - Define Time-to-Event (T2E)
- Safety-Critical Control (SCC)
 - Define Time-to-Hazard (T2H)
 - Set T2E and T2H timers
 - Schedule Tasks over Time-Sensitive Intelligent Modules (TSIM)
- Timer T2H << T2E:
 - TSIM tunes ML model to deliver before T2H
- Timer T2H = T2E
 - Fail-operational: SCC takes over





Crucial non-technical enablers:

- Resilience technologies (sustainability through threats)
- Laws and regulations (Europe is advanced here)







TAKE-AWAYS:



Ecosystem mindset

Laws and regulations, "no Far-West"

AV systems (AI/ML or other) cannot ignore distributed real-time systems and control theory

Accidents and attacks, safety and security

Reconciliation of uncertainty with predictability must be an inherent design predicate, not an after thought, a question of "training better"

Modular and technology neutral resilience solutions, from mechanical to cyber world



Q&A on Paulo's talk

- Good Q&A on the talk from Long
- Colleagues asked about whether some of the issues can be seen as perception failures rather than safety failures (though with the acknowledgment that the perception failures can lead to safety failures).
- Concerns that the (parts of) the automotive industry are not treating the safety issues seriously enough – and the philosophy of "move fast and break things" should not be used in safety-critical environments (including automotive cars).
- Several comments regarding the reconciliation of uncertainty with predictability, and ensuring that this is an inherent design predicate.



Thank you!

 Correction/editions/clarifications are welcome (from authors and audience).

