RS1: Securing the Autonomous System Usage Environment

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RS1 - Secure Usage of Autonomous Systems

Autonomous Systems (AS) are typically Cyber-Physical Systems (CPS) where malfunctions can lead to catastrophic consequences, such as loss of life or serious injury \rightarrow AS entail **safety-critical** functionality.



Engineering and Physical Sciences Research Council



RS-1B (2): Detecting Imperceptible Attacks

Similarity-based Deep Neural Networks (**Sim-DNN**) can be used to detect *imperceptible adversarial attacks* on the sensors (e.g. vision system) of AS.



Pros:

- These frameworks provide excellent results for various attacks.
- These methods require few

Cons:

- Weak adaptability and transferability to new domains, e.g., attacks or datasets.
- Slow training due to large model scales,



manual-engineering.

RS-1B (2): ML Domain Generalization Framework



- The feature extractor or detector is trained with a partner who is well tuned for different domains.
- In the test stage, the trained target feature extractor and detector are combined with the FFN to detect attacks in unseen domains.

RS-1A: RAFL- Dynamic & Compositional AS Security CRS-1A: RAFL- Experimental Results

• Develop a **robust and adaptive** federated meta-learning framework (**RAFL**)

RS-1A: The experimental results demonstrate that the proposed **RAFL** framework

resilient against adversaries.



Goals:

- Leverage distributed AS nodes to collaboratively train a global model to quickly adapt to new environments.
- Defend against adversarial attacks to reduce negative impact of attacks on ML models.

Key techniques:

- Federated meta-learning: Decentralized inner/out loops to train ML models.
- **Rule-based and Variational Autoencoder** (VAE) online learning-based detection model to detect adversarial attacks.
- A similarity-based model aggregation to conduct a global meta-model to further reduce the likelihood of uploading adversarial models from AS nodes.

is robust by design and outperforms other baseline defensive methods against adversaries in terms of model accuracy and efficiency.



RS-1B (1): Safe Decision Making in AS

Establishing **safe and secure** operation of an AS in uncertain and dynamic environments is part of the focus of our research in **RS-1B** (*Explainable and Verifiable* Decision Making). We have undertaken a survey of specifications of AS, focusing on formal specification.

CRS-1B (1): Safe Decision Making in AS

RS-1B(1): We have implemented a *proof obligation generator* for checking continuous inductive invariants (the proof obligations are discharged using the SMT solver **Z3**) and are currently engaged in integrating it with the **TLA+ Toolbox**. Enables a convenient way of proving safety of continuous systems within the formal framework of the TLA+ Toolbox and will support formal verification of CPS.

• Formal modelling and verification of CPS is highly challenging, but can help in providing very strong guarantees about the behavior of AS.





- We are working towards adding support for reasoning about CPS in the formal verification framework of **TLA+** based on Lamport's Temporal Logic of Actions.
- Formal methods can provide *verifiable solutions* to trustworthy decision making in AS.



- RS-1A: Develop a mobility-aware adaptive machine learning framework
- RS-1B (1): Formal specification of AS Safety and Security
- RS-1B (1): Case studies of safety verification of CPS in the TLA+ Toolbox. Integrate proof obligation generator into the Proof Manager in TLA+ Toolbox.
- RS-1B(2): Visualization results of the proposed algorithm will be completed.
- RS-1B(2): Adaptability and transferability will be evaluated in real-world photos.







This work is supported by the Engineering and Physical Sciences Research Council [grant number: EP/V026763/1]