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Beyond Conventional Triggers: Auto-Contextualized Covert Triggers for Android Logic Bombs

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AGENDA

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Logic Bombs and Hidden Triggers

02

SensorBomb Framework

03

Prototypes and Attack Performance Analysis

04

Evasion Evaluations and Conclusion

Logic Bombs and Their Influence

- Logic bombs represent a class of condition-triggered malicious code that remains dormant until specific conditions are met

- Real-world Impact: Logic bombs have caused significant damage to different infrastructures

Android Logic Bombs and Existing Detection

- Logic bombs keep evolving by leveraging new trigger types to evade detection
- Both dynamic and static analysis have evolved accordingly to detect new triggers
- Now empowered by ML models, they can detect a wide range of potential triggers
- Academic attention to the topic has declined

Trigger Types

- Common conditions
- System events/property
- Context-aware property
- Communication/signal

Dynamic Fuzzing

- Botnet Detection [2008]
- Droidfuzzer [MoMM 2013]
- Dynodroid [FSE 2013]
- Intellidroid [NDSS 2016]

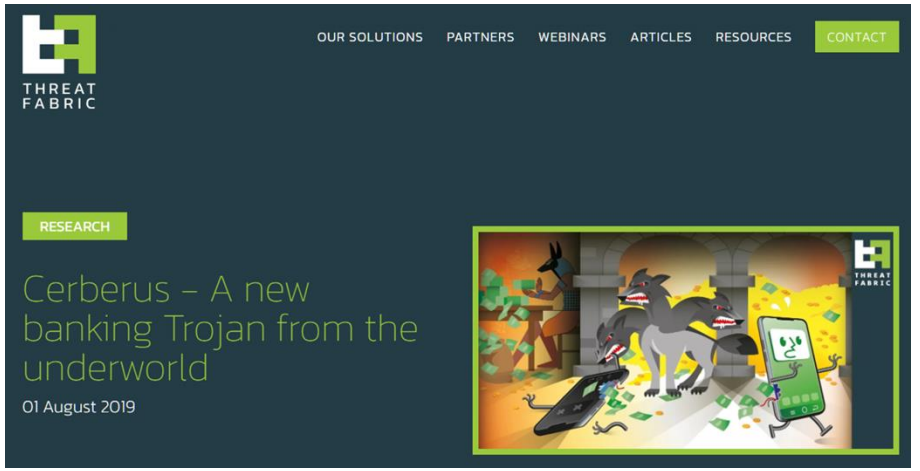
Static Analysis

- TriggerScope [S&P 2016]
- HSOMiner [NDSS 2017]
- BareCloud [USENIX SEC 2014]
- InputScope [S&P 2020]
- Difuzer [ICSE 2022]

Sensor-based Logic Bomb

- Some sensor-based logic bombs had evaded static analysis and had been released.

RQ1: how can sensor-based logic bomb evade static analysis reliably?

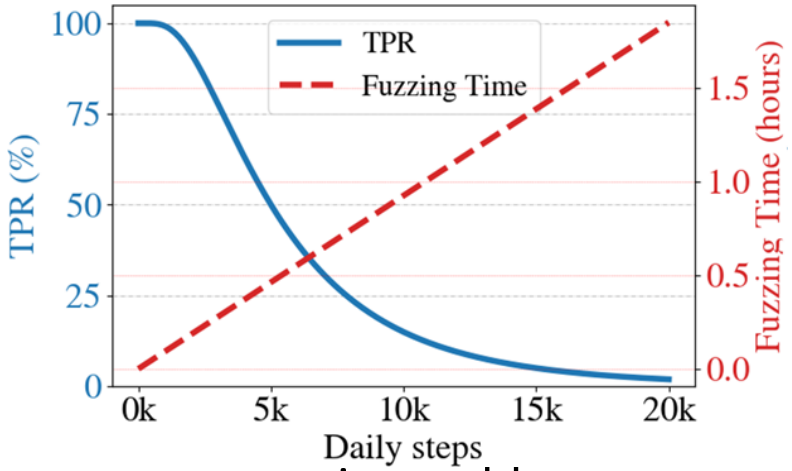


- We tested common sensors and sensitive operations they triggered by state-of-the-art logic bomb static detector Difuzer [1], some of which can indeed evade Difuzer.

HSO	contacts	calls	photos	location	microphone	network	Bluetooth	SMS
Accelerometer	√	√	√	√	√	√	√	√
Camera	√	X	√	√	√	√	X	X
Motion sensor	X	X	√	X	√	√	√	X

[1] J. Samhi, L. Li, T. F. Bissyandé, and J. Klein, "Difuzer: Uncovering suspicious hidden sensitive operations in android apps," in Proceedings of the 44th International Conference on Software Engineering, 2022, pp. 723–735.

Sensor-based Logic Bomb



- Sensor reading-based logic bomb
  - It is easy to fuzz
    - Sensors always have limited reading range
  - Low success rate
    - In the real world, attackers always satisfy success rate to remain stealthy

RQ2: how to leverage controlled dynamic-pattern-based trigger to be resistant to fuzzing test while keeping high trigger success rate

- Sensor-state-based anomaly detection has been proposed to detect all attacks leveraging sensors (e,g., 6thsense [1] and Sbtddl [2])

RQ3: how to evade sensor-state-based anomaly detection

[1] K. Sikder, H. Aksu, and A. S. Uluagac, "{6thSense}: A context aware sensor-based attack detector for smart devices," in 26th USENIX Security Symposium, 2017, pp. 397–414.

[2] S. Manimaran, V. Sastry, and N. Gopalan, "Sbtddl: A novel framework for sensor-based threats detection on android smartphones using deep learning," Computers & Security, vol. 118, p. 102729, 2022.

Auto-Contextualization

Device Contextualization for controlled dynamic-pattern-based trigger

Static Contextualization for static detection evasion

RQ1: resistant to static analysis

- Mimic legitimate sensor use

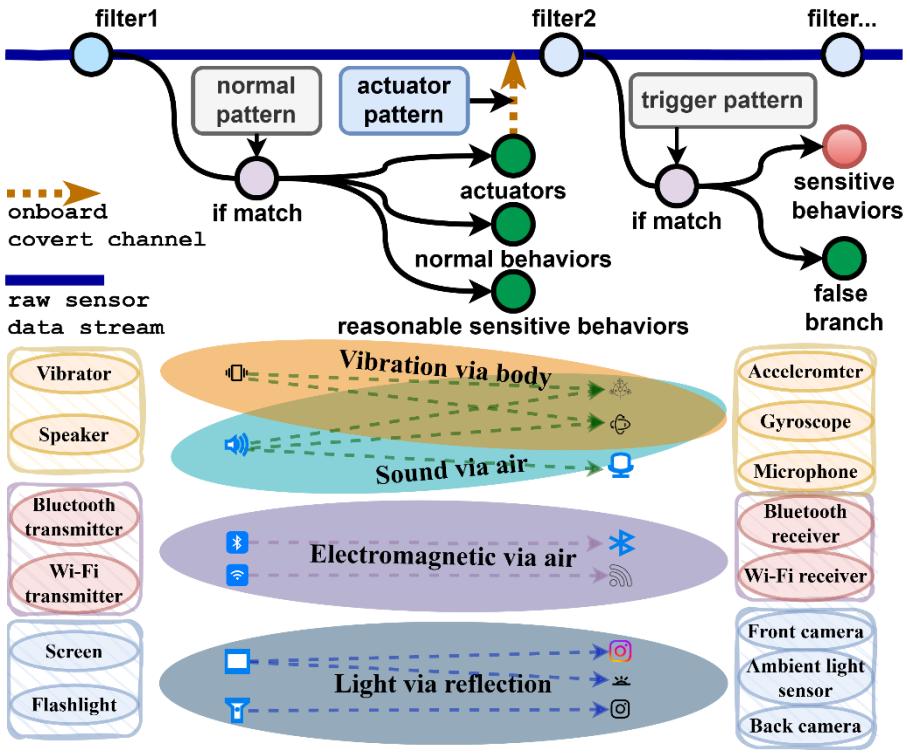
RQ2: controlled dynamic-pattern-based trigger

- Onboard actuators
- Dynamic trigger patterns
- Onboard sensor-actuator covert channel discovery

RQ3: evade sensor-state-based anomaly detection

- Measure actuator's influence on sensor readings
- Mimic legitimate actuator behavior

Behavior Contextualization for anomaly detection evasion



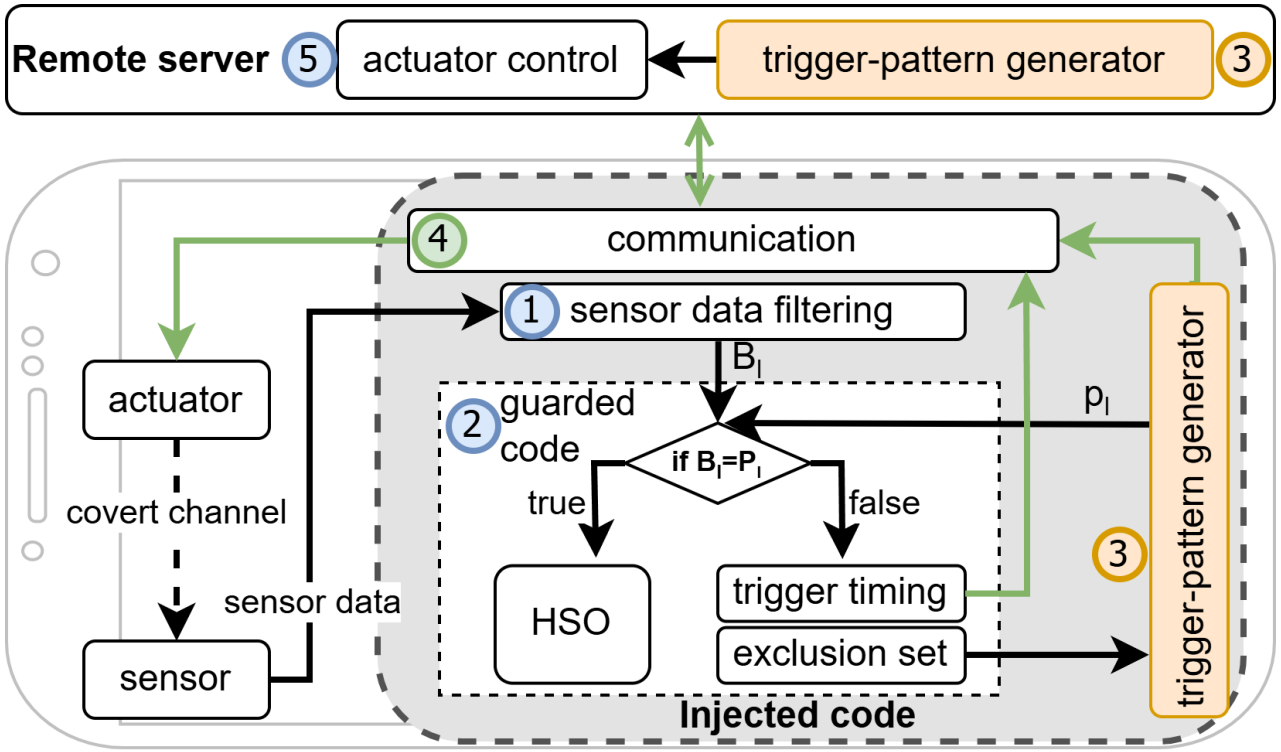
BPF and threshold-based filtering

Category	Trigger Condition	Source / Mechanism	Vibration Pattern	Semantic Intent
Fitness & Tracking	Goal achieved (steps, distance)	Background metric threshold	Short celebratory multi-pulse	Positive reinforcement
	Lap / segment completed	Distance/time threshold event	Single medium pulse	Progress milestone feedback
	Start / pause / resume / stop	Foreground UI action	Short pulse / dual-tap (pause)	Mode transition acknowledgment
	HR zone / arrhythmia alert	HR sensor + rule evaluation	Repeated short pulses	Physiological safety warning
	Inactivity reminder	Step counter + periodic timer	Soft gentle pulses	Behavioral nudging

Auto-Contextualization Components

1 Device Contextualization for Data Filtering

- Automatically configure the parameters of the onboard covert channels and the filters.
- Based on device specifications and knowledge base
- Knowledge base: parameters of existing covert channels through different media



Parameters:

- band-pass filter BPF(f)
- time window W(Δt)
- threshold θ

Example:

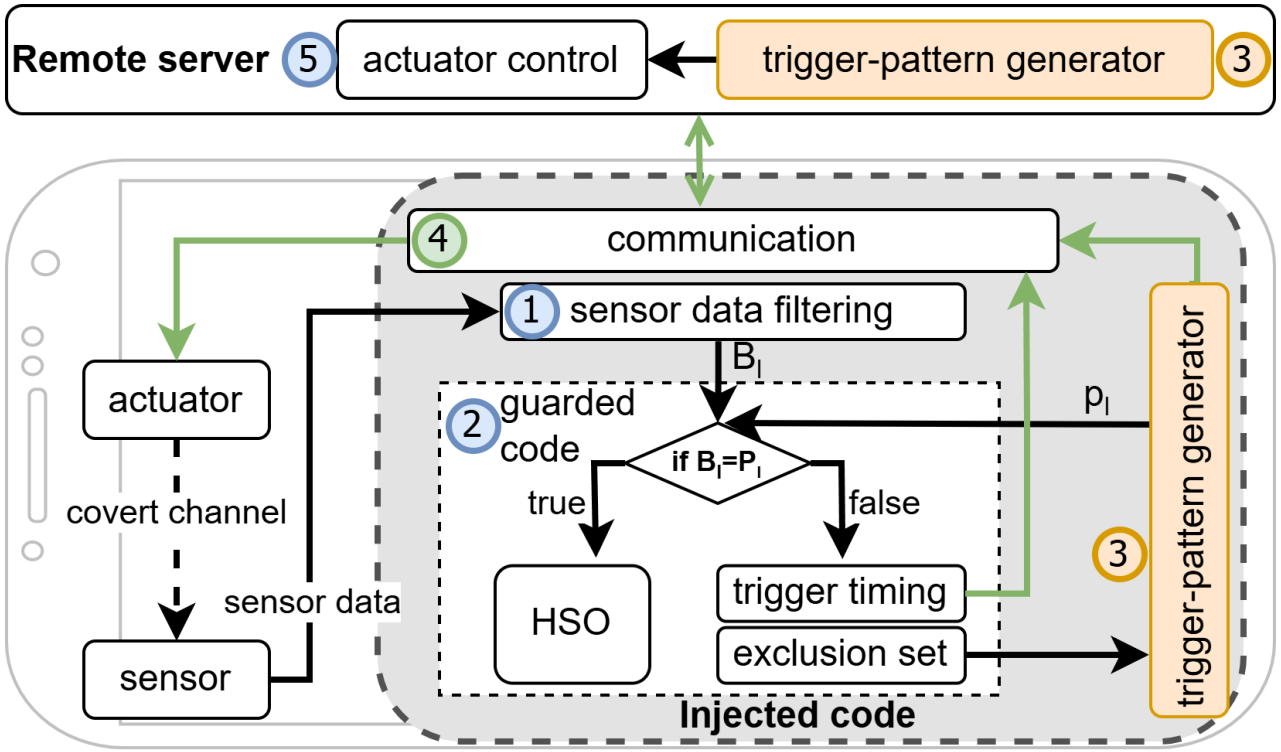
The vibration pattern [100, 200, 200, 100]

-> Binary codes 100110

Auto-Contextualization Components

2 Host App Contextualization for Guarded Code Generation

- Automatically select the sensitive methods that can evade static analysis.
- Based on the host app category, sensor type, and knowledge base.
- Infer real-time sensor status and statistical patterns.

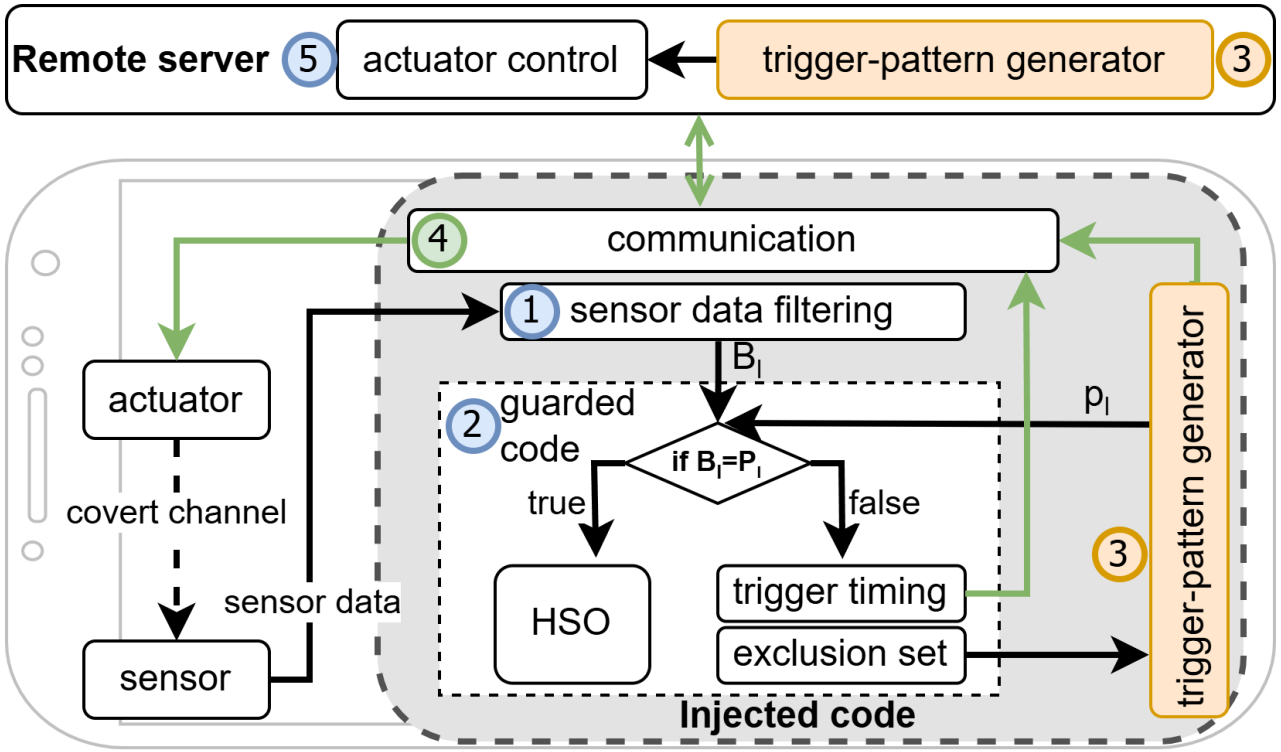


- **Static evasion**
  - Alignment: sensitive methods, number of app methods, number of sensitive methods
- **Trigger pattern exclusion**
  - Record all mismatch triggers -> patterns generated in daily behaviors
- **Optimal timing**
  - When all observed bits are zero -> no interference

Auto-Contextualization Components

3 Pattern Generation

- Optimal pattern length balancing transmission errors, false triggers, and fuzzing space
- Generate dynamic pattern to evade fuzzing test based on records
- Mimic legitimate actuator behaviors to evade anomaly detection



Optimal Pattern Length (l):

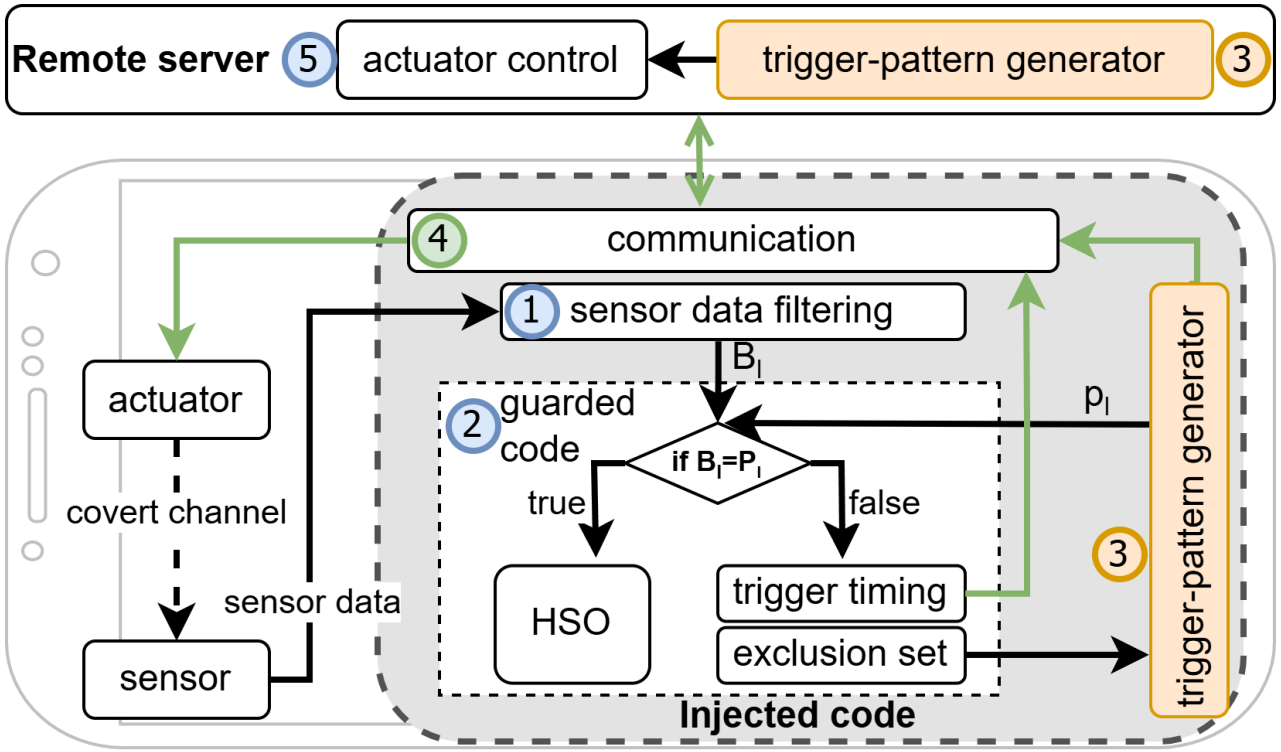
$$l^* = \arg\max_{l \in \mathcal{L}} \; w_d\,(l \ln 2) - w_f\, e^{-\alpha l} - w_e\left[1-(1-p)^l\right]$$

- p is the channel BER
- α is the exponential decay rate
- w_d, w_f, and w_e are weights
- $L = [l_{min}, l_{max}]$ denotes the soft boundary

Auto-Contextualization Components

4 Communication

- Device to server
  - Trigger timing and exclusion patterns
- Server to device
  - Command to control the actuators



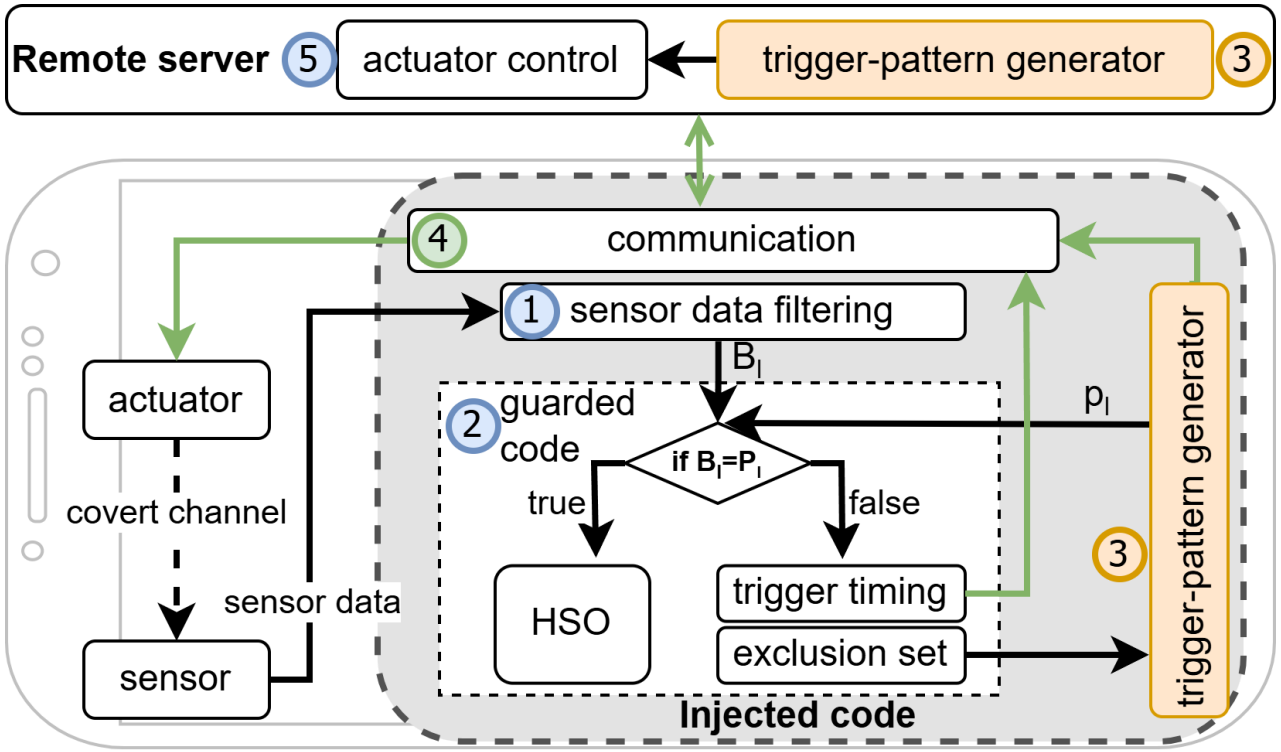
All traffic is transparent, and the content is not suspicious

- **Control actuators:**
  - JavaScript API or media content
- **Uploaded information:**
  - Plaintext and a small exclusion pattern set

Auto-Contextualization Components

5 Actuator Control

- Manage contextual and behavioral alignment to avoid user suspicion



- Contextual alignment
- Behavior alignment
- Controlled pattern variation

Example:

When a fit app meets an exercise goal, vibration notifications happen with a familiar pattern.

Evaluation Objectives

- Automated injection of SensorBombs and its robustness
- Attack success rate and false-trigger rate
  - Zero FTR and high ASR
- Resistance against static analysis, dynamic fuzzing test, and anomaly detection
  - High evasion rates

Evaluation Settings

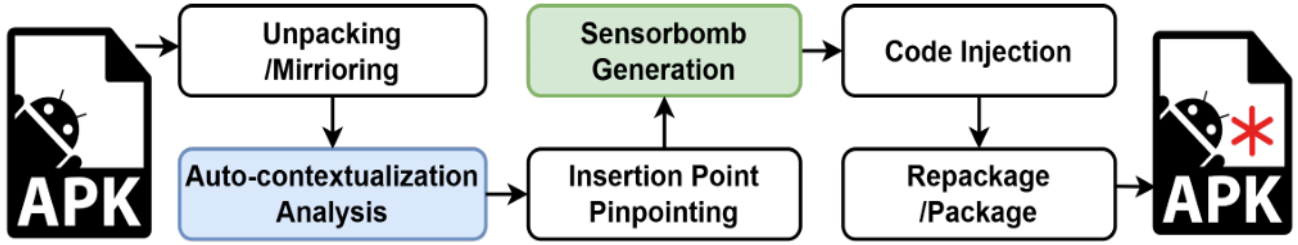
1. **Devices:** smartphones from 5 vendors with 7 models

Category	Brand	Model	API ver.	Max screen brightness	Screen size	Ratio	Vibrator axis
Low-end	Xiaomi	Mi 8	29	600 nits	6.2 in	2.08	Z-axis
	Samsung	S9	28	630 nits	5.8 in	2.06	Z-axis
	OnePlus	10T	30	950 nits	6.7 in	2.23	X-axis
	Motorola	Edge+	32	1000 nits	6.7 in	2.22	X-axis
Flagship	Samsung	S23+	33	1750 nits	6.6 in	2.17	X-axis
	Samsung	S24+	34	2600 nits	6.7 in	2.17	X-axis
	Vivo	x200	35	4500 nits	6.7 in	2.22	X-axis

2. **Large-scale injection:** injecting 3 types of triggers into 1,729 APKs from AndroZoo
3. **Prototypes:** self-developed Android apps based on three covert-channels
4. **Automatic testing: open-source** software, pipeline
5. **Manual testing:** 15 volunteers (college students under IRB)

Large-Scale Automated Injection

- **Injection pipeline**
  - APK filtering: 1,729 out of 5,000 APKs
  - Injecting using AndroBomb [1]

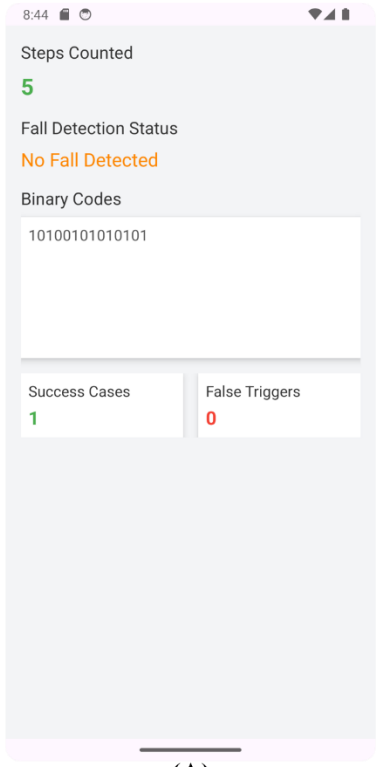


- **Testing pipeline**
  - Automatically testing: ADB-based script
  - Manual functionality checking
- **Results**
  - Successfully injected triggers into 1,403 APKs, and all passed ADB-based testing
  - Randomly selected 149 apps for manual checking and all passed the tests

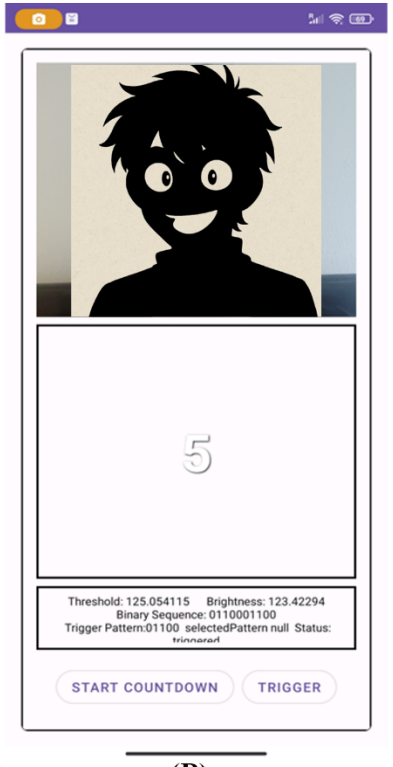
[1] J. Samhi, "AndroBomb (1.0)," 2022. [Online]. Available: https: //doi.org/10.5281/zenodo.5907924

Prototypes

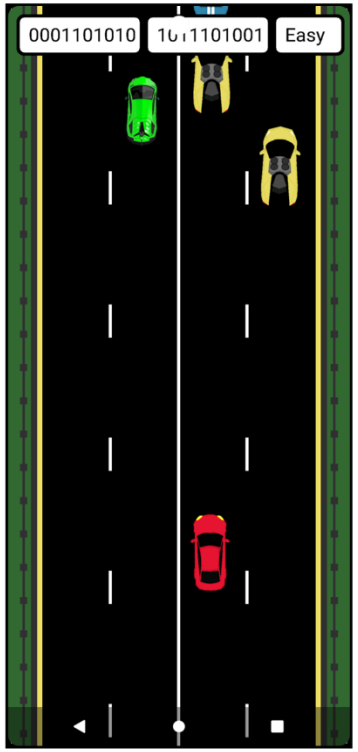
- **Accelerometer Bomb (A)**
  - Broadest attack class
- **Camera Bomb (B)**
  - Novel onboard covert channel
- **User Bomb (C)**
  - Comparison with existing real-world user behavior-based triggers



(A)



(B)



(C)

SensorBomb	Host App	Sensor Data Filtering			Actuator Logic		Trigger Enhancement	
		f	Δt	θ	actuator	behavior logic	l	timing
Accelerometer bomb	step count & fall detection	$80-100Hz$	$>20ms$	fixed	vibrator	notification	$<17bits$	stable
Camera bomb	selfie	$1Hz$	$1s$	optimal	screen	counting down	3, 5, 10	low ambient light
User bomb	car racing game	$50Hz$	on difficulty level	automatic	user	user playing	unlimited	playing

Attack Success Rate and False-Trigger Rate

- **Accelerometer bomb experiment**
  - **12 common usage scenarios [1]:**

	Static Usage Scenarios						Moving Usage Scenarios					
Behavior	Stand	Sit	Talk-Sit	Lay	Stand-Sit	Pick	Jump	Push-up	Sit-Up	Run	Stair-Up	Table-tennis
Duration	1 min	1 min	1 min	1 min	1 min	1 min	1 min	1 min	1 min	1 min	1 min	1 min
Trigger /test times	10/10 (100%)	10/10 (100%)	10/10 (100%)	10/10 (100%)	9/10 (100%)	10/10 (100%)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
False trigger	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour	0/hour

  - **Results:**
    - 100% ASR due to accurate trigger timing
    - 0% false triggers due to statistics collection of false trigger patterns

[1] N. Sikder and A.-A. Nahid, "Ku-har: An open dataset for heterogeneous human activity recognition," Pattern Recognition Letters, vol. 146, pp. 46–54, 2021.

Additional Tests

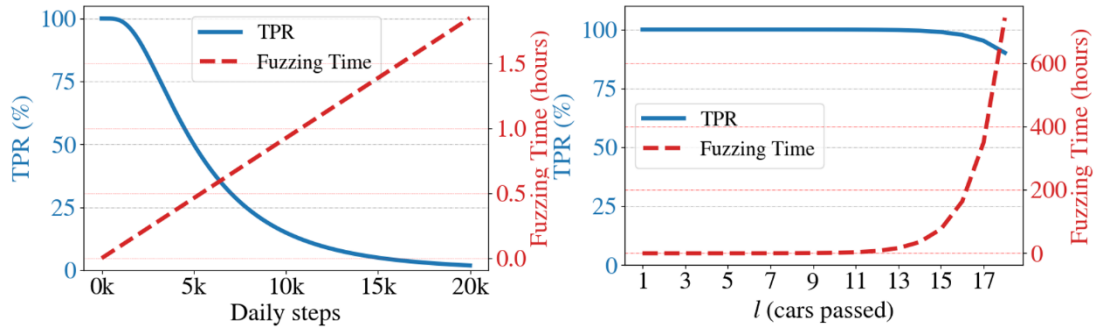
- **Camera and User bomb experiments**
  - **Camera bomb:** 5 common usage scenarios :

Scenarios		Dim bedroom	Normal light bedroom	Bright living room	Daylight office	Sunlight
Times/TPR	Low-end	120/100%	108/95.4%	8/87.5%	0/-	0/-
	Flagship	10/100%	10/100%	0/-	0/-	0/-
FPR	All	0%	0%	0%	0%	0%

  - **Results:**

    100% ASR and 0% false trigger under dim light conditions

  - **User bomb:** 15 volunteers playing a car racing game :



  - **Results:**
    - 700 hours fuzzing time while 90% success rate

Resistance to Detection

- **Evasion from static detector Difuzer [1]**
  - Y means selected by SensorBomb,
  - N means not;
  - ✓ means successfully evade Difuzer
  - × means not.

HSO	contacts	calls	photos	location	microphone	network	bluetooth	SMS
Acc bomb	Y | ✓	Y | ✓	Y | ✓	Y | ✓	Y | ✓	Y | ✓	Y | ✓	Y | ✓
Cam bomb	Y | ✓	N | ×	Y | ✓	Y | ✓	Y | ✓	Y | ✓	N | ×	N | ×
User bomb	N | ×	N | ×	Y | ✓	N | ×	Y | ✓	Y | ✓	Y | ✓	N | ×

- Results:
  - 100% evasion rate

[1] J. Samhi, L. Li, T. F. Bissyandé, and J. Klein, "Difuzer: Uncovering suspicious hidden sensitive operations in android apps," in Proceedings of the 44th International Conference on Software Engineering, 2022, pp. 723–735.

Sensor Data Fuzzing Evasion

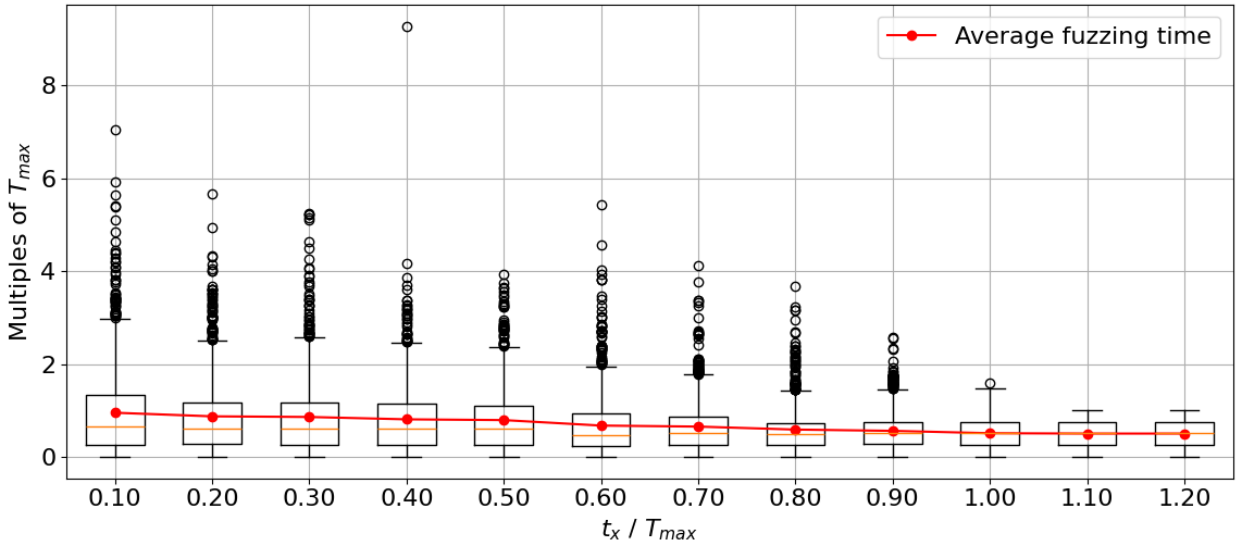
- **Theoretical Estimation**
  - We adopt a data-sweeping strategy to cover the full parameter space
  - SensorBomb variants > 100 hours
  - Sensor-reading variants ~2 hours

SensorBomb	n_θ	n_f	l (bits)	Δt (s)	T_{max}
Acc bomb	fixed	fixed	13–16	0.02–0.06	104.2 hours
Cam bomb	2	20	3, 5, 10	1	115.8 hours
User bomb	fixed	fixed	16	0.5	145.6 hours
Sensor value	**range**		**scale**	**sampling rate**	T_{max}
Ambient light [61]	0–188,000 lux		0.045 lux	50 Hz	2.32 hours
Step count [18]	0–20,000 steps		1 step	3 steps / s	1.85 hours

- **Experimental Results**
  - SensorBomb variants:

    They need more fuzzing time than theoretical estimation
  - Sensor-reading variants:

    They match the theoretical estimation



Anomaly Detection Evasion

- **Evasion from sensor-status based anomaly detection SBTDDL [1]**
  - LSTM detector
  - 12 common usage scenarios [2]:

	Static Usage Scenarios						Moving Usage Scenarios					
Behavior	Stand	Sit	Talk-Sit	Lay	Stand-Sit	Pick	Jump	Push-up	Sit-Up	Run	Stair-Up	Table-tennis
Evasion times/rate	10/10 (100%)	10/10 (100%)	10/10 (100%)	10/10 (100%)	9/10 (100%)	10/10 (100%)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)

  - Results:
    - 100% evasion rate

[1] S. Manimaran, V. Sastry, and N. Gopalan, "Sbtddl: A novel framework for sensor-based threats detection on android smartphones using deep learning," Computers & Security, vol. 118, p. 102729, 2022.

[2] N. Sikder and A.-A. Nahid, "Ku-har: An open dataset for heterogeneous human activity recognition," Pattern Recognition Letters, vol. 146, pp. 46–54, 2021.

Conclusion

- **Auto-Contextualized Triggers:** Novel approach that dynamically adapts to device and application context, moving logic bomb design from leveraging new triggers to deep hiding by Auto-Contextualization
- **Comprehensive Evasion:** Successfully bypasses static analysis, anomaly detection, and dynamic fuzzing test
- **Practical Validation:** Three working prototypes and large-scale injection test demonstrate real-world feasibility
- **Systematic study:** To our knowledge, it is the first systematic study of sensor-based logic bomb evasion

Thank You!

Read our paper:

Personal website:

Potential Countermeasures

- **Actuator Regulation**
- A whitelist to allow only actuator patterns found in legitimate apps
  - 98% adopted patterns consistent with common patterns
  - Fuzzing may be employed to detect the trigger
  - The attacker may still combine multiple benign patterns as a trigger
  - Pattern-based whitelist is changing for multimedia-related actuators. Such as screens and speakers.
  - Limit the device output levels.

Out of Scope Detection

- **Repackaging Detection**
  - Signature verification, integrity check.
- **Signature-Based Detection**
  - Large-scale injection will leave footprint
- **Communication Content**
  - Transmission of a small set of binary codes
  - The set is very small, e.g., 138 12-bit binary code in accelerometer bomb

Static Analysis Tools

- **TriggerScope [1]:**
  - Limited to predefined triggers (time, location, SMS)
  - High false positive rate when adding sensors to the trigger types
- **HSOMiner [2]:**
  - No public code and dataset
- **Difuzer:**
  - Open-source code

[1] JordanSamhi, “Tsopen,” https://github.com/JordanSamhi/TSOpen, 2021, accessed: 2025-12-12.

[2] X. Pan, X. Wang, Y. Duan, X. Wang, and H. Yin, “Dark hazard: Learning-based, large-scale discovery of hidden sensitive operations in android apps.” in NDSS, 2017.