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Resilient Cognitive Systems – Document

Safety-Team 1

Contents

Introduction

The primary objective of this project is to develop and optimize a safety concept for a robotic arm that interacts with humans in various analysis scenarios. The core challenge lies in ensuring that the robot operates efficiently, while maintaining safety by stopping immediately when a human enters its vicinity.

Project Goals and Constraints

Following the guidelines of the Resilient Cognitive Systems challenge, we considered the following factors:

- **Safety Criticality:** Any scenario resulting in the robot touching a human leads to a score of zero.
- **Sensor Economy:** While one camera is provided, additional sensors can be integrated at the cost of the overall score.
- **Environmental Adaptability:** The system must remain robust across diverse contexts, including varying light conditions, different human appearances and crowded environments.
- **Infrastructure Limitations:** External safety measures like physical fences or light barriers are strictly prohibited.

Methodology

To ensure a comprehensive safety concept, we employed the following frameworks:

- HARA-Analysis
- Fault-Tree Analysis
- CARE-Analysis
- Cause Tree

This document details our transition from a vulnerable, camera-only perception system to an improved, multi-sensor architecture designed to provide a high level of efficacy and resilience in human-robot interaction.

Content

HARA-Analysis

In order to provide a safety concept with the best possible coverage, we need to clearly define our system, including technical elements and actors involved.

For this, we used the HARA-Analysis introduced in our course. The HARA aims to define the scope of our system and provide a largely complete overview of factors involved by dividing them into 7 steps: The System, Persons at Risk, Hazards & Hazard types, Physical Properties, Actuator Failure Modes, Actuators and Failure Modes.

From there on, we used these categories to combine them into HARA-guide phrases to serve as exemplary hazard cases to countermeasure against.

To provide a proof of completeness for the HARA-analysis, we opted for a traceability matrix (Figure 1) that compares Physical Properties against all other HARA-categories, except for the actuators. The reason for this selection was that we were sure of the completeness of the two actuators in our system. Each Physical property could be traced back to one of the actuators that it affected and was therefore more likely to be complete as well. Reading the matrix from left to right provides the remaining guide-phrases.

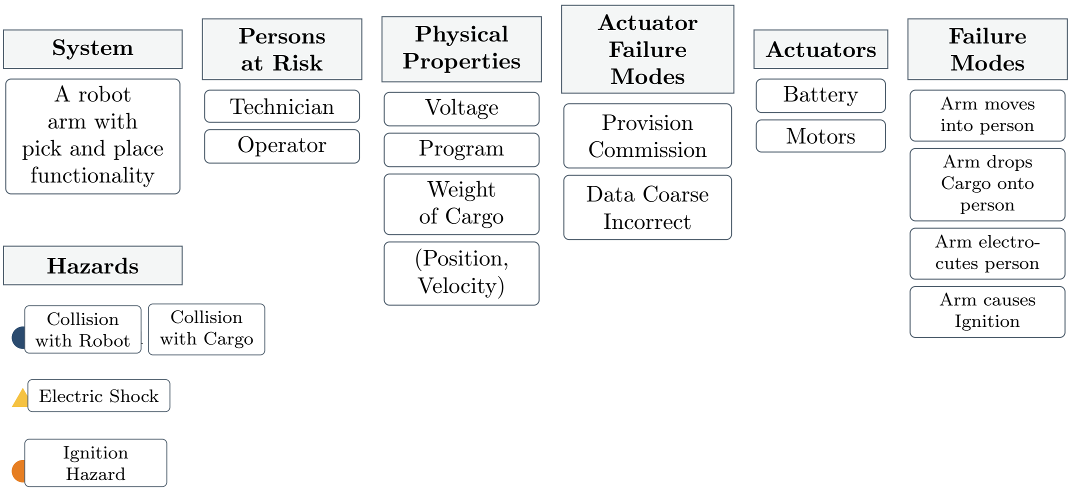


Figure 1: HARA System Definition Categories

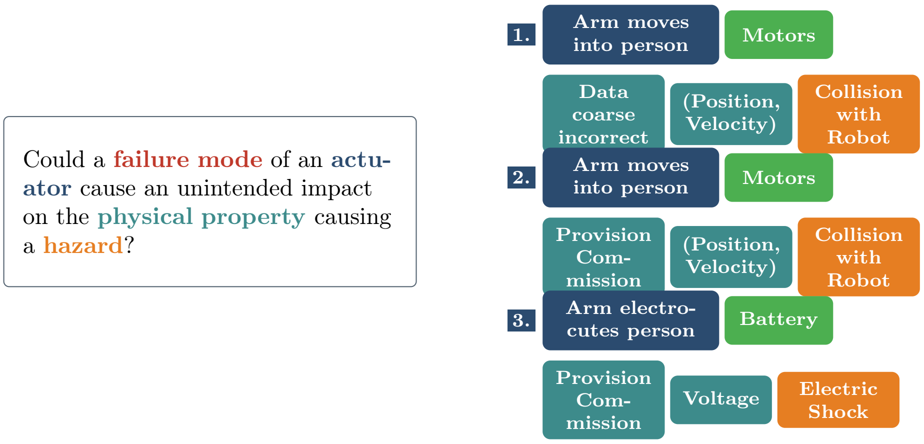


Figure 2: HARA Guide Phrases

Previous System Architecture

We define the robotic arm system in detail using a three-level architecture that takes in the arm's current position and the desired movement plan.

In the first level, we discern several elements:

- **Mission planner**, which receives a mission and outputs a target and object
- **Obstacle Detection**, which receives camera information and outputs an object list
- **Gripper Sensor**, which receives the grip strength and grip width and outputs the grip percentage and strength
- **Joint Motor Sensors**, which receive the position, velocity, and acceleration of the joint motors and output a vector consisting of the three numbers

At the second level, the **Trajectory Planner** receives the outputs and maps them to a trajectory consisting of the arm's current and next positions. Additionally, it outputs the time to destination.

The third level **Trajectory Control** transforms them into six different degrees for each joint motor of the robot arm, with one additional vector for the robot grip. This represents the actual movement of the arm to fulfil the mission.

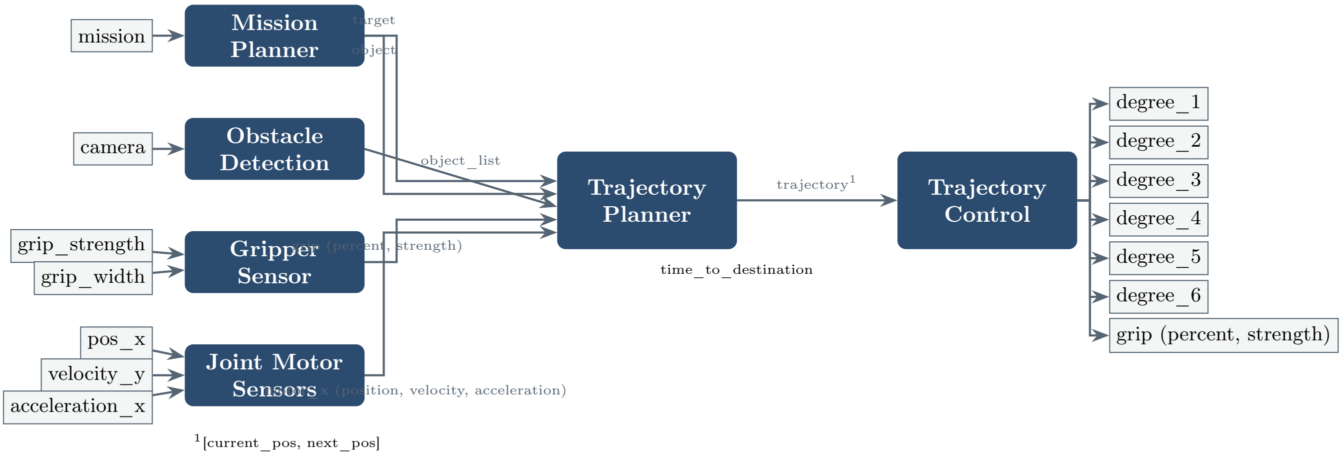


Figure 3: Previous System Architecture

Limitations with Previous System Architecture

However, camera-only perception cannot guarantee safe human detection due to variable visibility, signal degradation, and ambiguous interpretation by ML models. We defined three broad categories for limitations imposed on our previous System Architecture.

Physical limitations

- **Darkness, light fluctuations, and absorbent clothing** leads to insufficient light intensity reaching lens
- **Humidity, fog, rain, smoke** can distort optical signal
- **Occlusion, lens dirt, or misaligned camera** can block rays, leading to unusable signal

Sensing limitation

- **Quantization or clipping** can remove subtle cues or create course artifacts
- **Fast motion + exposure timing** can cause motion blur / rolling-shutter distortion
- **Fixed Pattern Noise, vibration, or power issues** can reduce SNR and corrupt frames

Computational limitations

- **Out-of-distribution scenes** and unseen circumstances can cause omission or false activation
- **Reflection, pictures or person-like background** patterns can trigger provision commission
- **Biased training data and learned shortcuts** cause poor generalization

Figure 4: Limitations with Previous System Architecture

Fault-Tree Analysis - Gottlieb

We analysed the architecture level by level to identify every possible fault. For this we defined our top fault "robot arm moves even though it should not" as degree of motor x is too high.

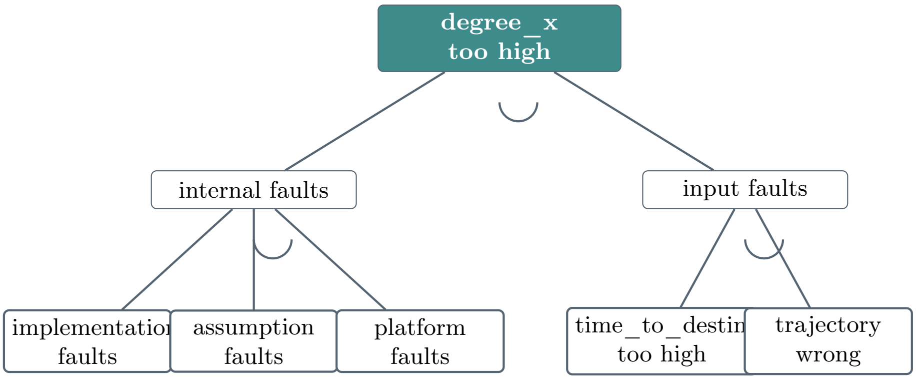


Figure 5: Fault-Tree Analysis

CARE-Analysis

CARE adds structure for perception and actuation analysis by subdividing it into single steps that provide a basis for systematic analysis and coverage. In the following, we will focus only on the sense half of the model, as our system is detection-oriented. The analysis is subdivided into four steps. Each step provides a source, a model, the model's assumptions, a sink, an insufficiency backlog, and some exemplary analysis cases. For completeness, each step is accompanied by a traceability matrix that matches Assumptions to Failure Modes.

- **C->A:** We examine insufficiencies that might occur and lead to differences between the actual value and the sensed value, causing erroneous detection. (Figure 2 + 3 in Appendix)
- **A->R:** We examine insufficiencies that might occur and lead to differences between the actually sensed value and the digital representation of the value, causing erroneous detection. (Figure 4 + 5 in Appendix)
- **R->E:** We examine insufficiencies that might occur and lead to differences between the digital representation of the value and the estimated value, causing erroneous detection. (Figure 6+7 in Appendix)

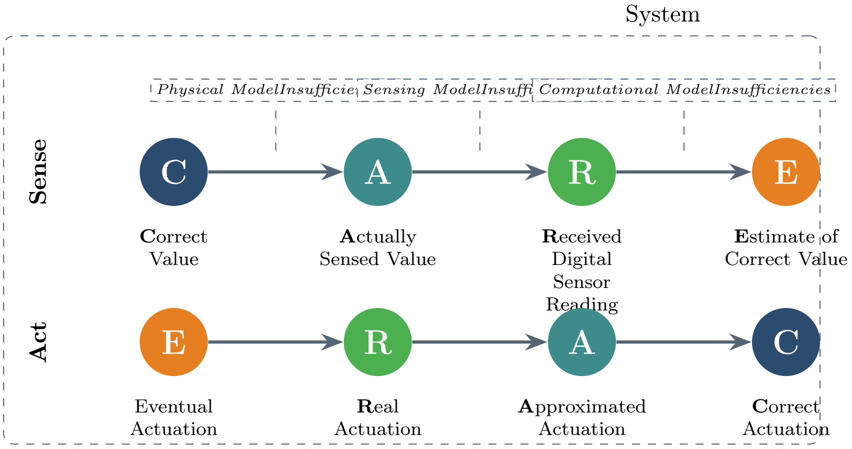


Figure 6: CARE Analysis Model

Cause Tree – Jan

Based on the results of the HARA, fault-tree, and CARE analyses, we derive a cause tree to systematically explain how a person in the hazard zone may remain undetected.

At the highest level, the unwanted event can occur either because a valid image is available but misinterpreted by the computational model, or because the image is already insufficient at the model input. These two branches directly map to the CARE structure. Computational model insufficiencies occur during the R→E step and include cases in which available digital data is incorrectly interpreted due to biased or insufficient training data, limited model capacity, or inappropriate runtime thresholds and decision logic.

In contrast, insufficient model input is further decomposed into sensing and physical model insufficiencies. Sensing model insufficiencies correspond to the A→R step and describe failures in sensing and digitization, such as limited dynamic range or quantization, inadequate temporal sampling or exposure, sensor noise, spectral mismatch, or preprocessing that removes relevant details. Physical model insufficiencies reflect the C→A step and describe violations of real-world assumptions at the optical input, for example, due to unfavorable lighting, unexpected appearance or reflectance of a person, environmental influences on light propagation, or geometric constraints such as occlusion or a limited field of view. The cause tree highlights recurring insufficiencies across the CARE layers, which directly define the points addressed by the proposed safety concept.

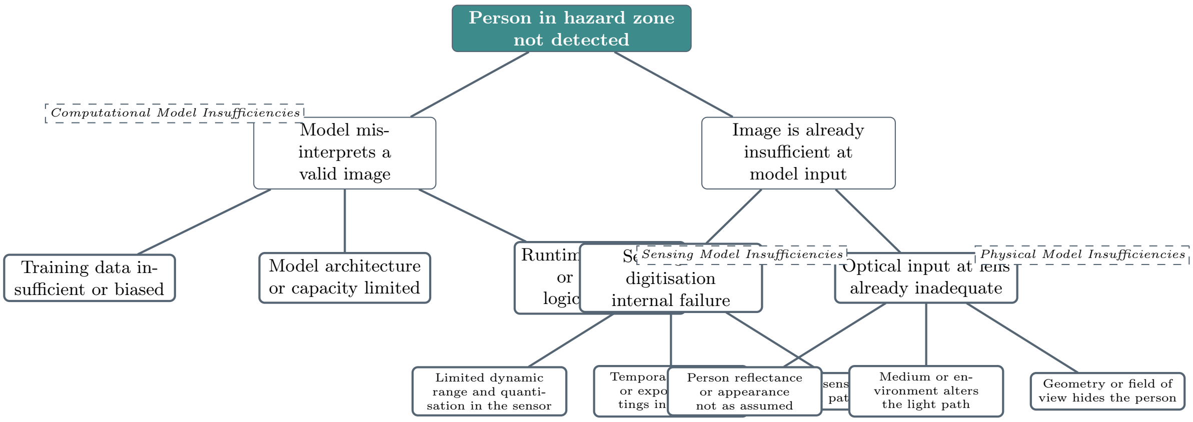

Person in hazard zone not detected
Computational Model Insufficiencies
Model mis-interprets a valid image
Image is already insufficient at model input
Training data in-sufficient or biased
Model architecture or capacity limited
Runtim or logic
Se digitisation internal failure
Sensing Model Insufficiencies
Optical input at lens already inadequate
Physical Model Insufficiencies
Limited dynamic range and quanti-sation in the sensor
Tempora or expo tings in
Person reflectance or appearance not as assumed
sens pat
Medium or en-vironment alters the light path
Geometry or field of view hides the person

Figure 7: Cause Tree

Improved Safety Concept - Lennard

To move away from our previous Safety Concept/Architecture, which relied solely on camera vision and had severe limitations, we opted for a dual-sensor setup. In addition to the optical camera data, the Object Detection element receives readings from a mmWave sensor. Depending on the readings, it either outputs an empty object list, indicating it will not stop, or an array containing the position of the detected movement, leading it to stop all movement.

When the mmWave detects movement = false, it outputs an empty array directly to the object list. If detects movement = true, we determine how far away the movement is. If it is greater than 2 meters away we once again pass on an empty array list, since the object is too far away to stop. If it closer than 2 meters we pass on an array with the position of all movement.

In the next step, we determine whether the detected movement was from a robot or not. For that we use the optical data from the camera. In order for a robot to be identified we use both a QR-Code for detection and a Classification trained on recognizing robots. If both these measures are true, an empty array list is passed to the Object list, since we do not want to stop when robots interact with each other. However, if only one of these measure returns false, we decide that a non-human entity is detected and we stop just in case by passing the position of all movement to the Object List.

CARE Analysis of Improved Safety Concept - Gottlieb

Evidence of Efficacy – Gottlieb

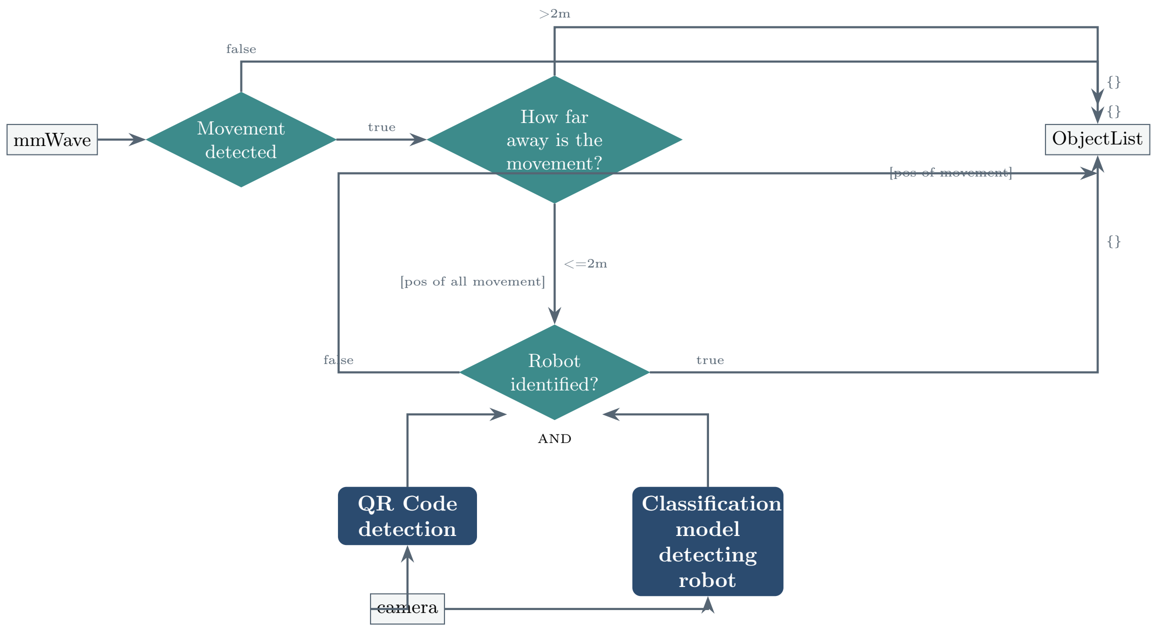
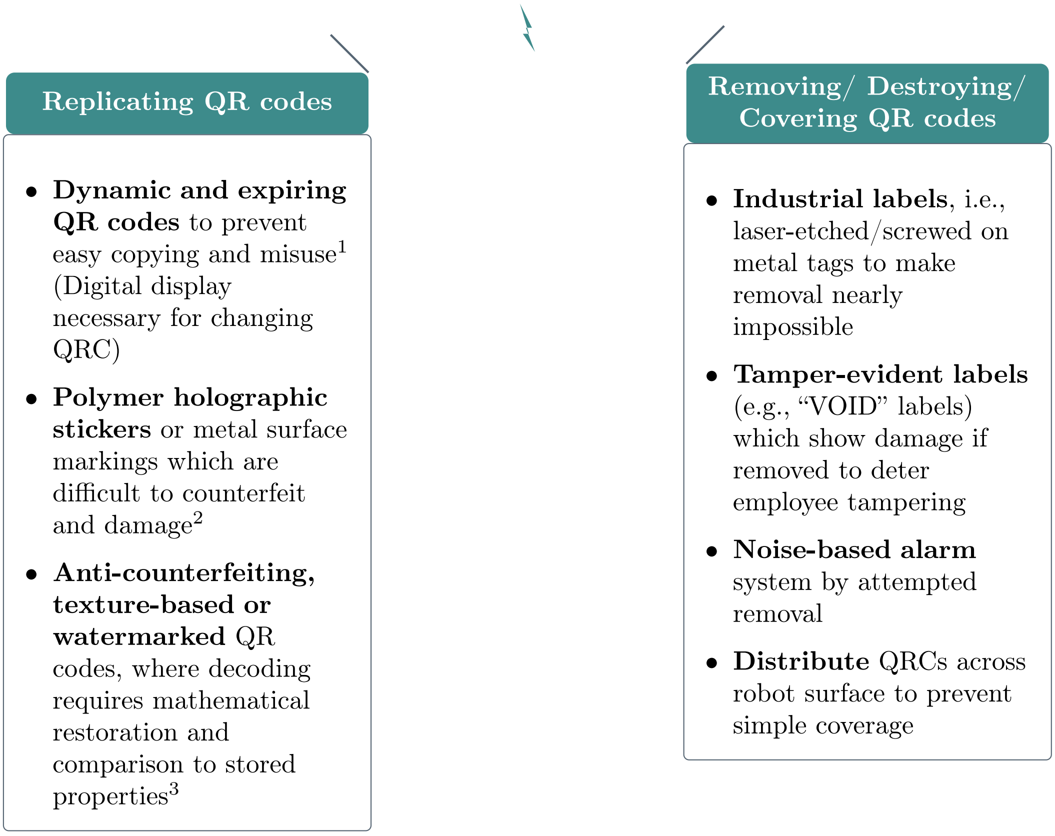


Figure 8: Improved Safety Concept - Evidence of Efficacy

Limitations & Countermeasures – Jan

Measures against QR-Code Tampering

To ease concerns about workers' misuse of robot QR code identification, we propose various countermeasures to prevent replication and destruction of the QR codes.



Replicating QR codes

- **Dynamic and expiring QR codes** to prevent easy copying and misuse[1] (Digital display necessary for changing QRC)
- **Polymer holographic stickers** or metal surface markings which are difficult to counterfeit and damage[2]
- **Anti-counterfeiting, texture-based or watermarked** QR codes, where decoding requires mathematical restoration and comparison to stored properties[3]

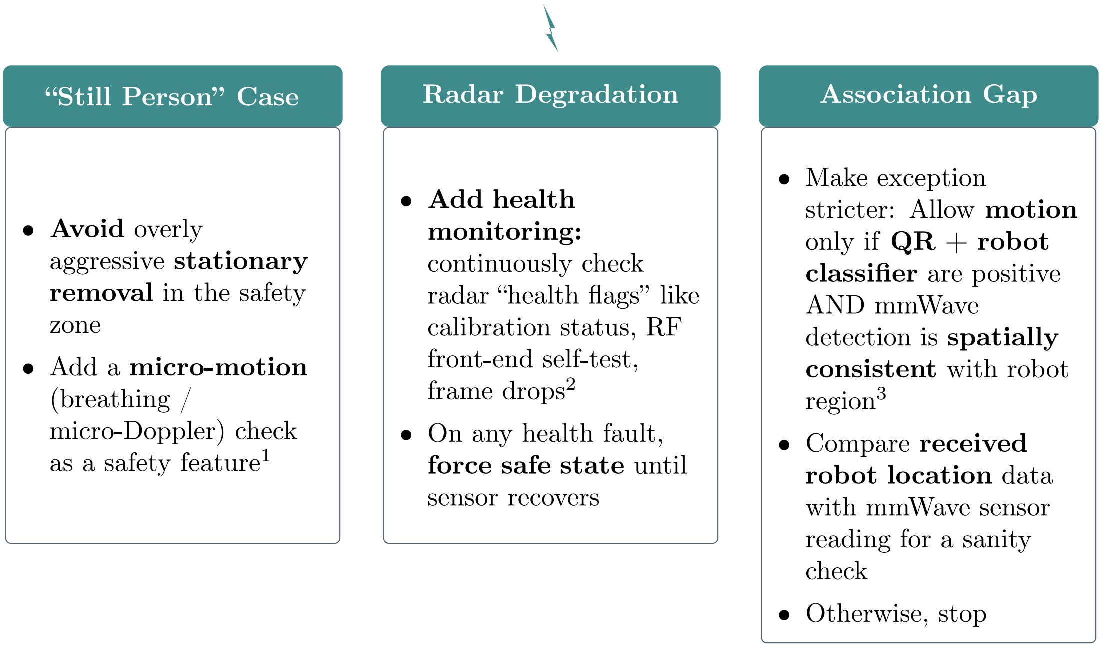
Removing/ Destroying/ Covering QR codes

- **Industrial labels**, i.e., laser-etched/screwed on metal tags to make removal nearly impossible
- **Tamper-evident labels** (e.g., "VOID" labels) which show damage if removed to deter employee tampering
- **Noise-based alarm** system by attempted removal
- **Distribute** QRCs across robot surface to prevent simple coverage

Figure 9: Measures against QR-Code Tampering

Measures against Provision Commission

For the remaining Provision Commission Issues, we propose the following measures to enhance the safety of our system further.



"Still Person" Case

- **Avoid** overly aggressive **stationary removal** in the safety zone
- Add a **micro-motion** (breathing / micro-Doppler) check as a safety feature[1]

Radar Degradation

- **Add health monitoring:** continuously check radar "health flags" like calibration status, RF front-end self-test, frame drops[2]
- On any health fault, **force safe state** until sensor recovers

Association Gap

- Make exception stricter: Allow **motion** only if **QR** + **robot classifier** are positive AND mmWave detection is **spatially consistent** with robot region[3]
- Compare **received robot location** data with mmWave sensor reading for a sanity check
- Otherwise, stop

Figure 10: Measures against Provision Commission

Business Case

Safety Demo – Jonathan

Appendix

Table 1: Appendix Figure 1: HARA Traceability Matrix

HARA Categories		**FM_1**	**FM_2**	**FM_3**	**FM_4**
Physical Properties		Actuator Failure Modes	Actuators	Hazard	Failure Mode
PP_1	Voltage, Current, Power	Provision Commission	Battery	Electric Shock, Ignition Hazard	Arm electrocutes a person, static discharge leads to a

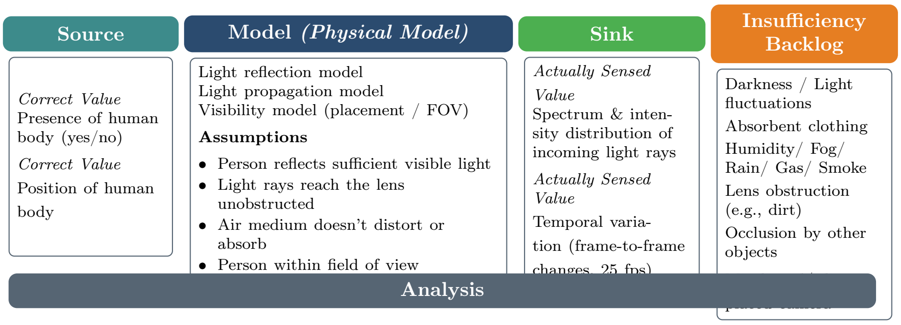
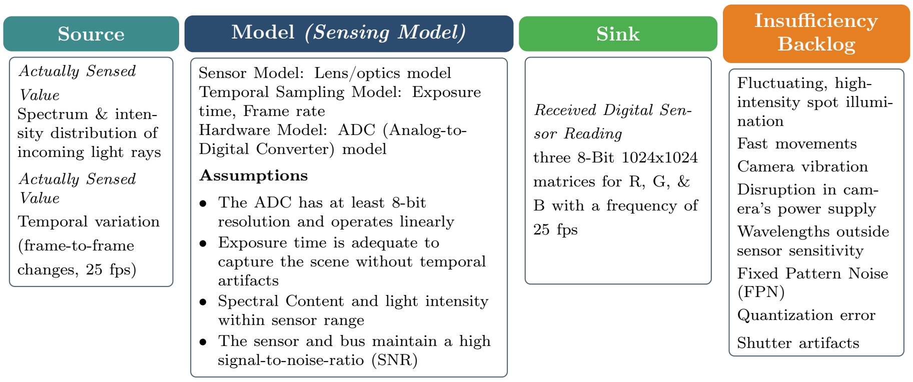

Source
Model *(Physical Model)*
Sink
Insufficiency Backlog
Correct Value
Presence of human body (yes/no)
Correct Value
Position of human body
Light reflection model
Light propagation model
Visibility model (placement / FOV)
Assumptions
• Person reflects sufficient visible light
• Light rays reach the lens unobstructed
• Air medium doesn't distort or absorb
• Person within field of view
Actually Sensed Value
Spectrum & intensity distribution of incoming light rays
Actually Sensed Value
Temporal variation (frame-to-frame changes, 25 fps)
Darkness / Light fluctuations
Absorbent clothing
Humidity/ Fog/ Rain/ Gas/ Smoke
Lens obstruction (e.g., dirt)
Occlusion by other objects
Analysis

Figure 11: Appendix Figure 2: C -> A Analysis

Table 2: Appendix Figure 4: C -> A Traceability Matrix

	Failure Modes	**FM$_1$**	**FM$_2$**	**FM$_3$**	**FM$_4$**	**FM$_5$**	**FM$_6$**
Assum		Timing Late	Timing Early	Provision Commission	Provision Omission	Data Subtle	Data Coarse
A$_1$	Person reflects sufficient visible light	TC$_{11}$: Person steps from darkness into light	TC$_{12}$: Sudden glare or specular reflection before person enters area	TC$_{13}$: Highly reflective background objects (= person-like features)	TC$_{14}$: Person wearing dark, non-reflective clothing (absorbent material)	TC$_{15}$: Low reflectance clothing and low ambient light/darkness	TC$_{16}$: Overexposure / bloom (strong direct light) saturates pixels
A$_2$	Medium doesn't distort or absorb	TC$_{21}$: Fog or steam dissipates just before detection	TC$_{22}$: Rain or water distortion leads to illusion of smaller distance	TC$_{23}$: Dense rain droplets produce bright/dark patterns that mimic person	TC$_{24}$: Thick fog or heavy rain attenuates person signature	TC$_{25}$: Light haze or high humidity blurs edges and reduces contrast	TC$_{26}$: Dense dust/smoke creates large textured blobs & coarse shapes
A$_3$	Light rays reach the lens unobstructed	TC$_{31}$: Temporary occlusion enters frame, delaying person detection	TC$_{32}$: Passing occlusion classified as person	TC$_{33}$: Transient reflections create person-like contours	TC$_{34}$: Obstruction of lens causes reduced or no feature visibility	TC$_{35}$: Thin film causes subtle blurring of person edges	TC$_{36}$: Lens heavily occluded/scratched; image shows large indistinct regions
A$_4$	Person within field of view	TC$_{41}$: Person enters the peripheral FOV first, only later moves into central detection zone	TC$_{42}$: Person silhouette appears momentarily at the edge, triggering detection early	TC$_{43}$: Background object with human-like vertical shape at the edge of FOV	TC$_{44}$: Camera is misaligned or displaced	TC$_{45}$: Person partially occluded by scene elements, only subtle features visible	TC$_{46}$: Person at extreme distance with low pixel footprint



Source

Actually Sensed Value
Spectrum & intensity distribution of incoming light rays

Actually Sensed Value
Temporal variation (frame-to-frame changes, 25 fps)

Model *(Sensing Model)*

Sensor Model: Lens/optics model
Temporal Sampling Model: Exposure time, Frame rate
Hardware Model: ADC (Analog-to-Digital Converter) model

Assumptions

- The ADC has at least 8-bit resolution and operates linearly
- Exposure time is adequate to capture the scene without temporal artifacts
- Spectral Content and light intensity within sensor range
- The sensor and bus maintain a high signal-to-noise-ratio (SNR)

Sink

Received Digital Sensor Reading
three 8-Bit 1024x1024 matrices for R, G, & B with a frequency of 25 fps

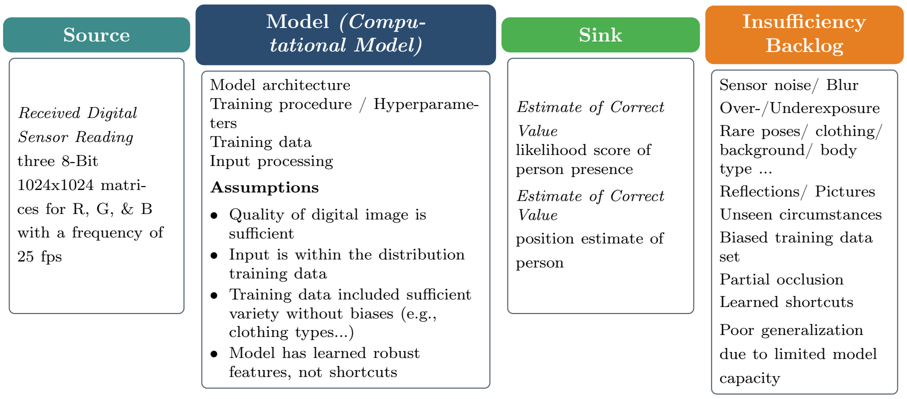
Insufficiency Backlog

Fluctuating, high-intensity spot illumination
Fast movements
Camera vibration
Disruption in camera's power supply
Wavelengths outside sensor sensitivity
Fixed Pattern Noise (FPN)
Quantization error
Shutter artifacts

Figure 12: Appendix Figure 3: A -> R Analysis

Table 3: A -> R Traceability Matrix

	Failure Modes	**FM$_1$**	**FM$_2$**	**FM$_3$**	**FM$_4$**	**FM$_5$**	**FM$_6$**
Assum		Timing Late	Timing Early	Provision Commission	Provision Omission	Data Subtle	Data Coarse
A$_1$	ADC has 8-bit resolution and operates linearly	TC$_{11}$: ADC auto-exposure + 8-bit quantization requires multiple frames to settle	TC$_{12}$: Quantization step noise or transient peak in a single frame	TC$_{13}$: Quantization artifacts or banding produce person-like edges/patterns	TC$_{14}$: 8-bit saturation removes subtle gradients that indicate a person	TC$_{15}$: Low bit depth causes low contrast for small/remote person pixels	TC$_{16}$: Severe quantization + dithering produces blocky/coarse pixel patterns
A$_2$	Exposure time is adequate to capture scene without temporal artifacts	TC$_{21}$: Readout hiccup / frame drop occurs during approach	TC$_{22}$: Frame duplication/ buffer replay presents stale frame	TC$_{23}$: Jitter in frame timestamp/ corrupted frames produce motion patterns	TC$_{24}$: High bus contention delays frame read-out, sensor to discards a new frame	TC$_{25}$: Rolling Shutter Distortion	TC$_{26}$: Read-out/ process aborted mid-frame due to system error, resulting in partial image frame
A$_3$	Spectral Content and light intensity within sensor range	TC$_{31}$: Sensor requires long exposure time due to low light	TC$_{32}$: Sensor has insufficient recovery time after severe light saturation	TC$_{33}$: Specific light wavelength is misinterpreted as a visible object	TC$_{34}$: Light intensity is too low to detect a person's presence.	TC$_{35}$: Scene contrast is lost due to specular reflection	TC$_{36}$: Extreme low light causes pixel values to be near zero (dark)
A$_4$	The sensor and bus maintain a high signal-to-noise-ratio (SNR)	TC$_{41}$: High SNR maintenance overhead delays the frame read-out	TC$_{42}$: High thermal noise causes buffer instability, leading to stale data reuse	TC$_{43}$: Fixed Pattern Noise (FPN) creates false person-like pixel artifacts	TC$_{44}$: Random noise obscures the subtle edges and features of a person	TC$_{45}$: High Noise level reduces effective dynamic range of person pixels	TC$_{46}$: Electrical noise spikes cause individual pixel values to become corrupted



Source	Model *(Computational Model)*	Sink	Insufficiency Backlog
Received Digital Sensor Reading three 8-Bit 1024x1024 matrices for R, G, & B with a frequency of 25 fps	Model architecture Training procedure / Hyperparameters Training data Input processing **Assumptions** • Quality of digital image is sufficient • Input is within the distribution training data • Training data included sufficient variety without biases (e.g., clothing types...) • Model has learned robust features, not shortcuts	*Estimate of Correct Value* likelihood score of person presence *Estimate of Correct Value* position estimate of person	Sensor noise/ Blur Over-/Underexposure Rare poses/ clothing/ background/ body type ... Reflections/ Pictures Unseen circumstances Biased training data set Partial occlusion Learned shortcuts Poor generalization due to limited model capacity

Figure 13: R -> E Analysis

Table 4: R -> E Traceability Matrix

	Failure Modes	**FM$_1$**	**FM$_2$**	**FM$_3$**	**FM$_4$**	**FM$_5$**	**FM$_6$**
Assum		Timing Late	Timing Early	Provision Commission	Provision Omission	Data Subtle	Data Coarse
A$_1$	Quality of digital image is sufficient	TC$_{11}$: Image sharpness improves only after several frames	TC$_{12}$: Early frame compression artifact or motion blur	TC$_{13}$: Noise, blur, or patterns resembling a person	TC$_{14}$: Image degraded (blur, smear, low resolution)	TC$_{15}$: Slight motion blur or defocus lowers feature clarity	TC$_{16}$: Severe compression, low resolution, or defocus
A$_2$	Input is within the distribution training data	TC$_{21}$: Out-of-distribution (OOD) scene causes model to hesitate	TC$_{22}$: OOD feature triggers early false activation	TC$_{23}$: Objects seen in training (e.g., mannequins, shadows) resemble humans	TC$_{24}$: Person outside training distribution (e.g., unusual clothing/ posture)	TC$_{25}$: Slight distribution shift (e.g., new camera angle, illumination, fisheye lens)	TC$_{26}$: Strong distribution shift (e.g., infrared illumination, fisheye lens)
A$_3$	Training data included sufficient variety without biases	TC$_{31}$: Under-represented groups (e.g., specific clothing colors)	TC$_{32}$: Model overfits to one feature, detects object with shared feature	TC$_{33}$: Shortcut in training, causing misidentification of background	TC$_{34}$: Under-represented demographics/ poses not recognized	TC$_{35}$: Features for a particular subgroup captured poorly	TC$_{36}$: Model generalizes poorly to certain body types or apparel
A$_4$	Model has learned robust features, not shortcuts	TC$_{41}$: Model depends on context features (e.g., shadows)	TC$_{42}$: Shortcut cue appears early	TC$_{43}$: Shortcut feature in background wrongly activates	TC$_{44}$: Shortcut fails, so the person is not detected	TC$_{45}$: Shortcut cue is partially present, model confidence fluctuates	TC$_{46}$: Shortcut-based model generalizes poorly