



Human Fall Detection: A Multimodal approach

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Outline

- Motivation
- Current systems
- Problems with unimodal system
- Multimodal strategy
- Dataset
- Experiments and Results
- Conclusion

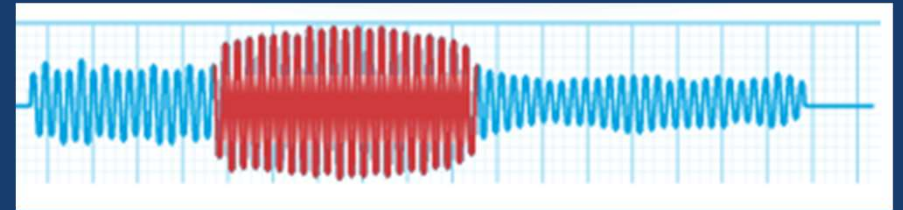
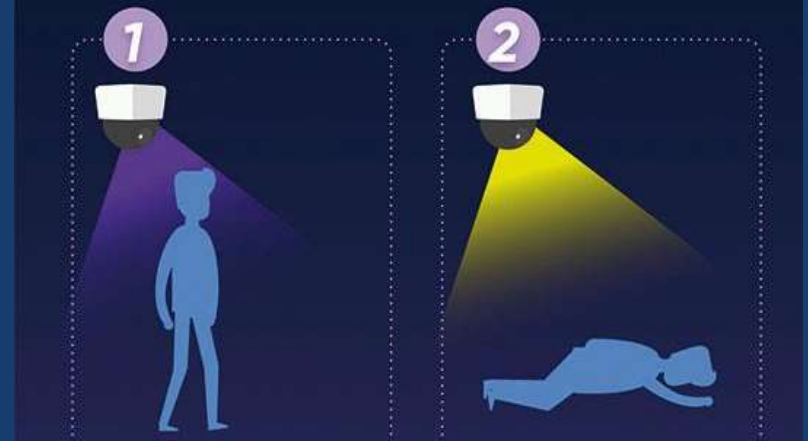
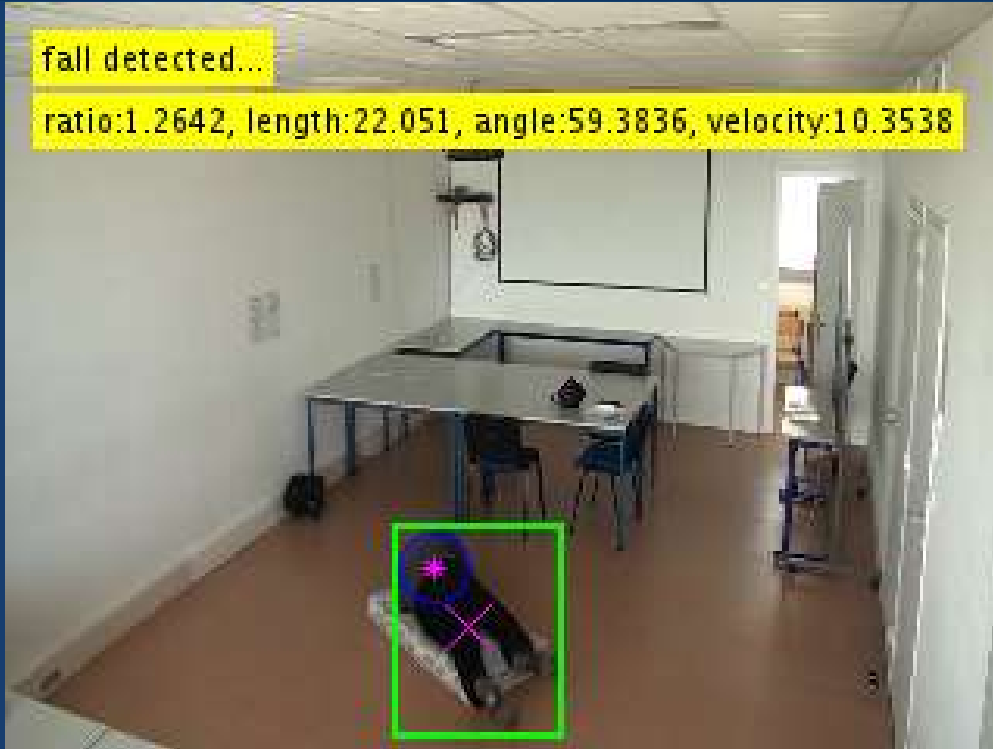


Motivation

- According to WHO fall is the leading cause of fatal and non-fatal injuries among elderly.
- According to demographic projections, the percentage of individuals aged 60 and above in the global population will almost double from 12% in 2015 to 22% by the year 2050.
- A timely assistance and recovery from fall is crucial.
- A late medical attention may lead to severe injuries or death.



Solution



Automatic, reliable, real-time fall detection system



Current Fall Detection Systems

Sensor-based systems

- Gyroscope
- Accelerometer

Visual Surveillance-based systems

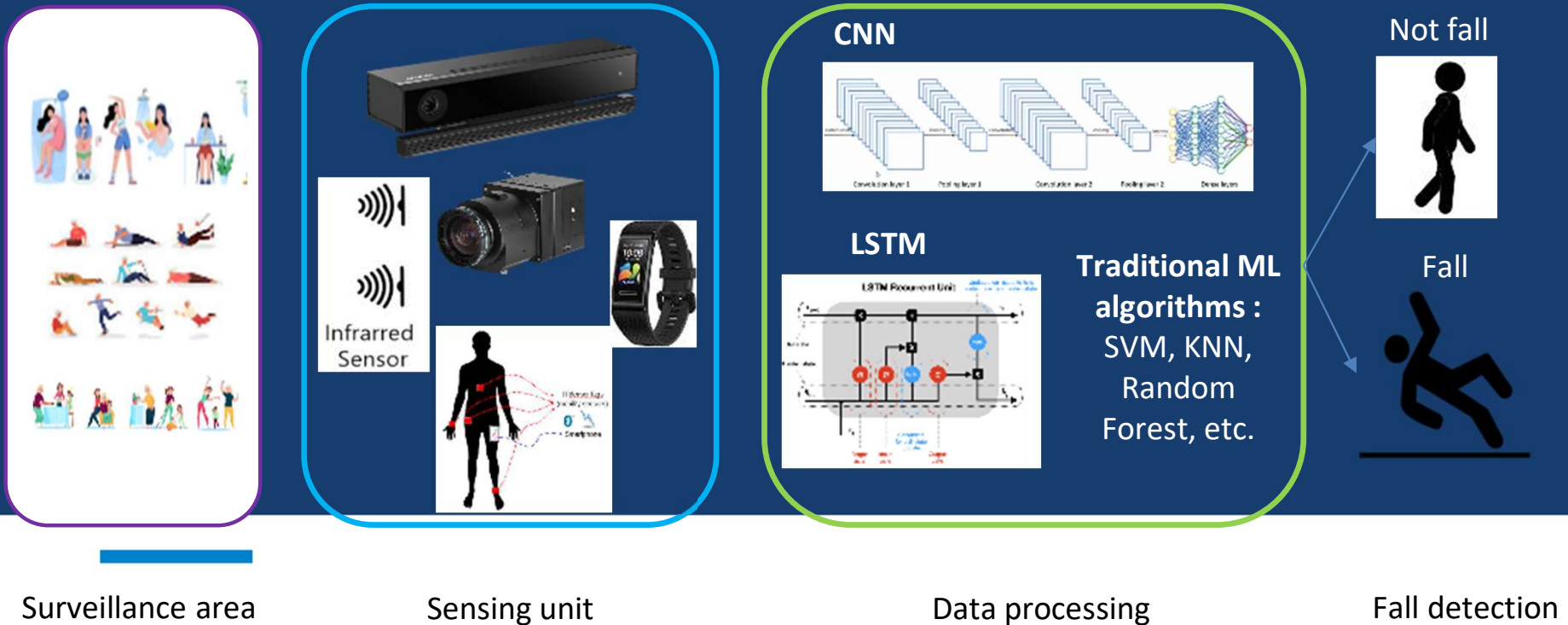
- RGB camera
- Depth camera
- Motion capture devices

Ambient systems

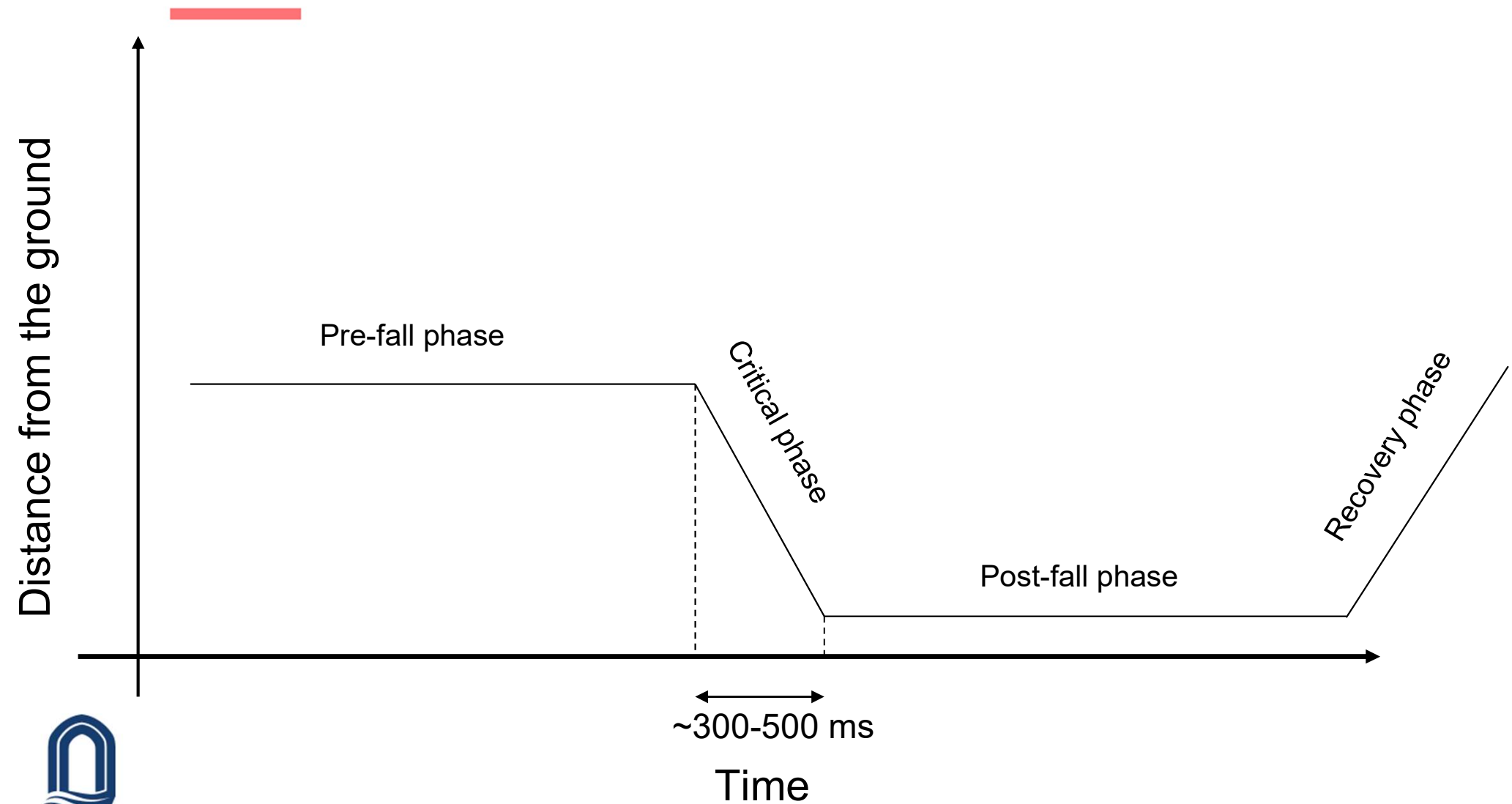
- Pressure sensors on the floor



General framework for a fall detection system



Falling down event: timing analysis



Unimodal systems characteristics

- Data collection and system training is quite easy
- It is relatively more cost effective
- The system accuracy and efficiency is limited
- Depending of the sensing unit, we may lose important information



(i) Z-fall, false negative



(k) Perpendicular-fall



(d) Scouting



(g) Bending, false positive

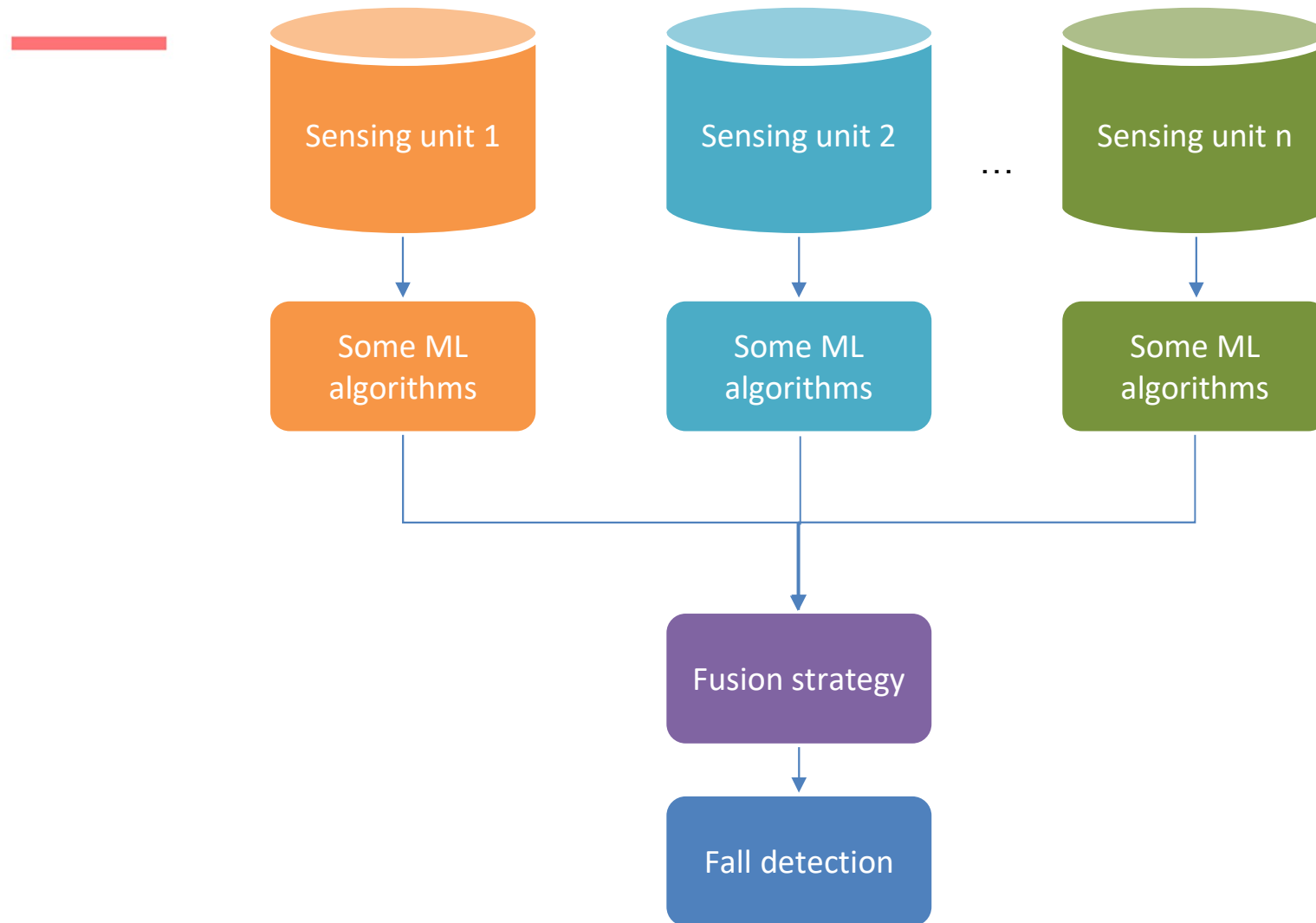


Multimodal systems characteristics and challenges

- Analyze data, find meaningful patterns and perform prediction by combining multiple heterogeneous sensing units
- Data collection will be more expensive and challenging (synchronization)
- The multimodal systems will be more accurate, efficient and robust to noises and errors
- Open question: How to fuse information from different sources?



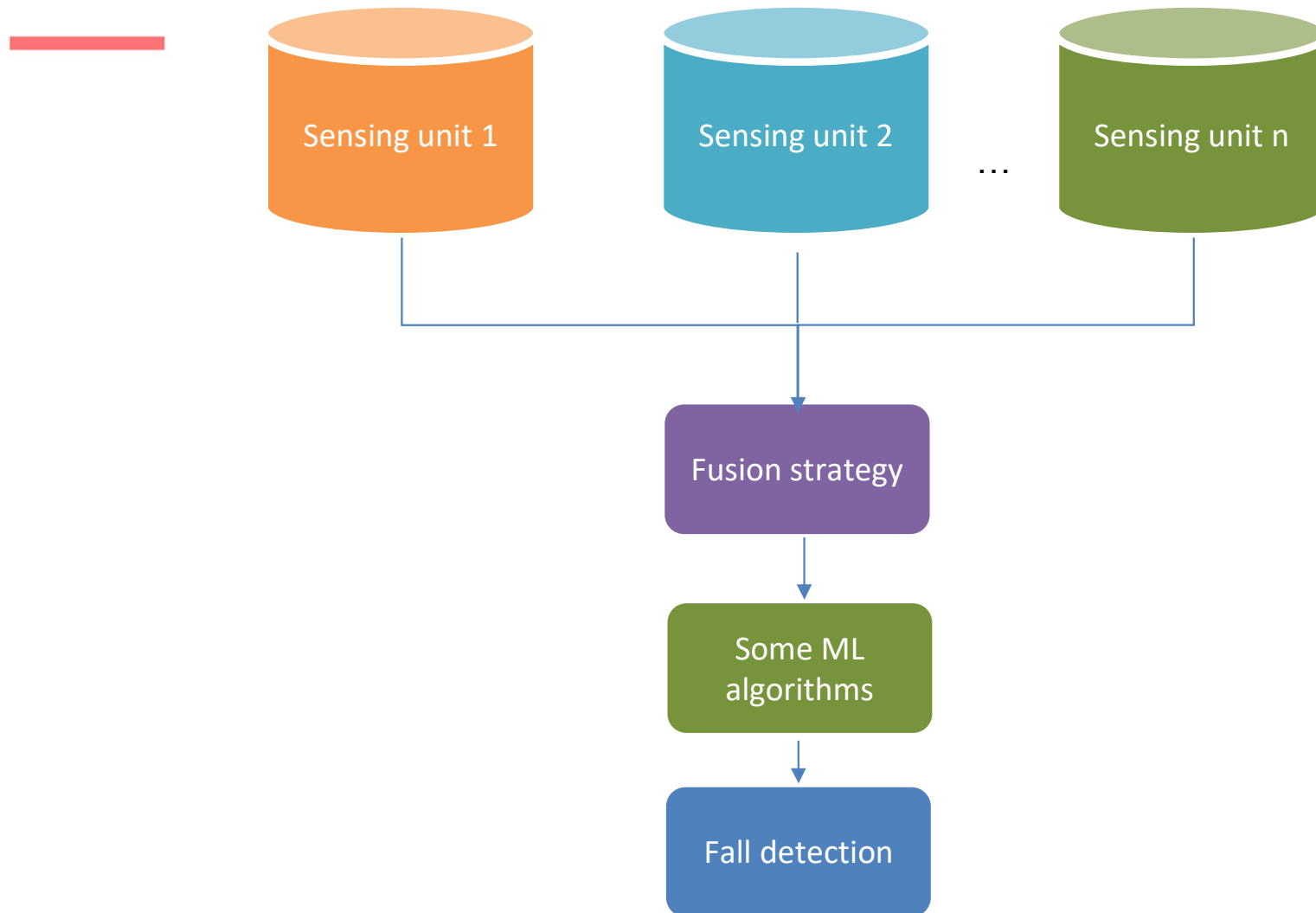
Fusion strategies



Late Fusion



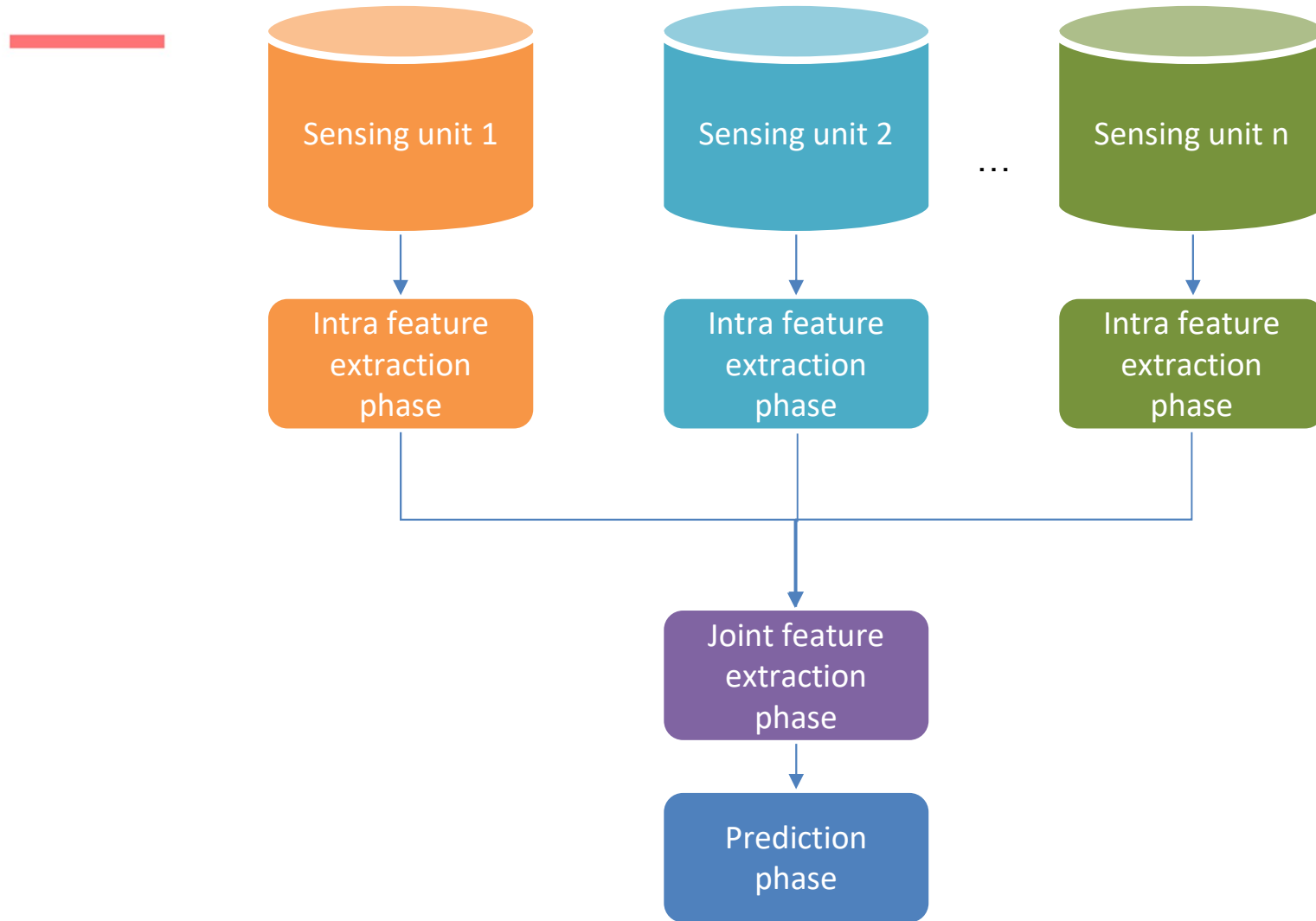
Fusion strategies



Early Fusion



Fusion strategies



Intermediate Fusion

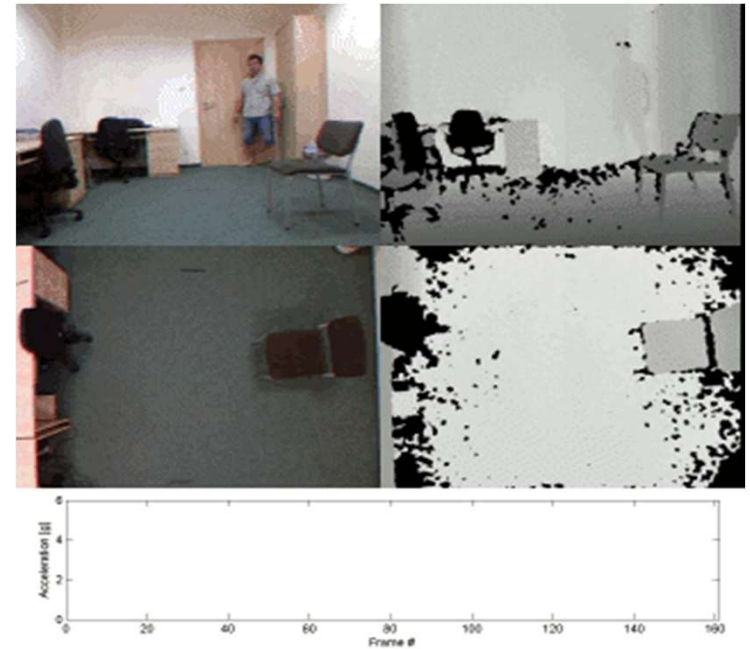


Dataset

UR fall detection dataset

Kwolek, B., & Kepski, M. (2014). Human fall detection on embedded platform using depth maps and wireless accelerometer. *Computer methods and programs in biomedicine*, 117(3), 489-501.

<http://fenix.univ.rzeszow.pl/mkepski/ds/uf.html>



Sensors model	No. subjects (F/M)	No. of samples (DLA/falls)	Position of sensors	Visual sensors	Action types (ADLs/Falls)	Fall Types
x-IMU (256Hz)	(0/5)	70 (40/30)	Near pelvis (waist)	<ul style="list-style-type: none"> • 2 Kinect cameras • 2 RGB cameras 	4/2	<ul style="list-style-type: none"> • falling from standing • falling from sitting



Data preparation

- Synchronization
- Data reshaping
- Resizing
- Normalization



Experiments Design

Experiment 1: ML model with early fusion

Training and testing phase using RGB + depth + accelerometer data.

Training using RGB + depth + accelerometer

Testing phase using only RGB + depth, and average accelerometer values for all 2995 frames.

Experiment 2: Baseline ML model

Training and testing phase using RGB + depth

Experiment	Variant	Precision	Recall	F1-score	Accuracy
1	i	0.97	0.96	0.97	97.25
	ii	0.94	0.98	0.96	94.99
2	i	0.91	0.99	0.95	95.16



Conclusion and future work

- A multimodal fall detection system is more efficient and accurate compared to a unimodal system
- A multimodal system with early fusion strategy is robust to the loss of sensing units
- More studies and experiments are needed to compare early fusion and intermediate fusion strategy



THANK YOU

