EAGER: A cloud-assisted Framework For Improving Pedestrian Safety in Urban Communities using Crowd-sourced Mobile and Wearable Device Data

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Research Goal

Design of an *effective* ***pedestrian safety system*** to ***prevent*** significant threats ***distracted pedestrians*** pose to themselves and others in the vicinity.

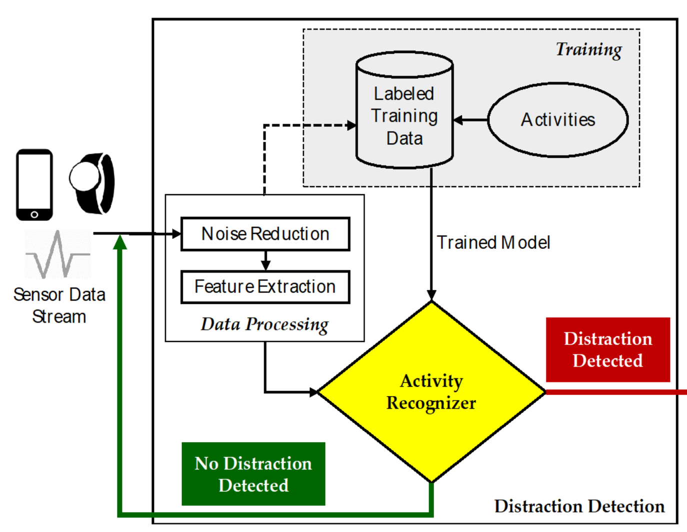
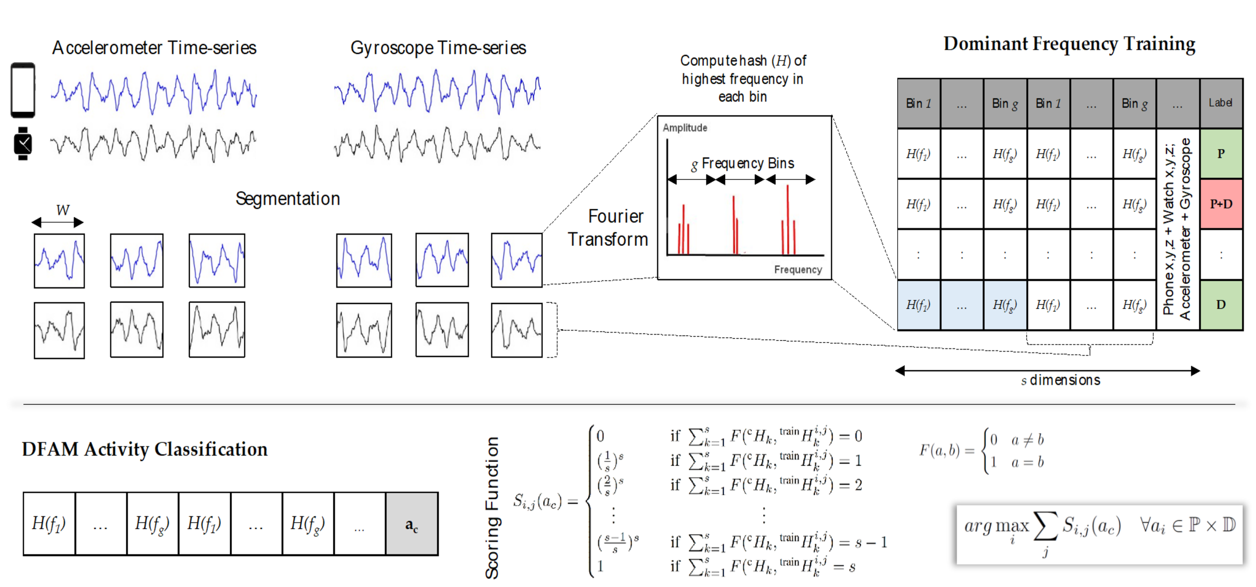


Figure: A generic pedestrian safety framework

Task 1: **Detect** Pedestrian **Distractions**

- Dominant frequency-based activity matching **(DFAM)** to detect distracted pedestrian activities.
- A **hierarchical** distracted activity recognition **framework** to reduce response time.



Experimental Setup

- ***14 distracted activities****: Reading, eating, using smartphone, or drinking* ***while*** climbing stairs, walking or running.
- ***20 participants*** with smartphone on the wrist and a paired smartphone in their front trouser pocket.
- **4** smartphone-smartwatch **placements**.

Observations

Multi-participant DFAM compared with Support Vector Machine (**SVM**), Decision Trees (**DT**), Random Forests (**RF**), Naive Bayes (**NB**), k-Nearest Neighbors (**k-NN**).

	DFAM	SVM	DT	RF	NB	1-NN	2-NN	3-NN
W = 32	0.49	**0.56**	0.45	0.53	0.49	0.53	0.52	0.54
W = 64	0.52	**0.65**	0.53	0.64	0.58	0.54	0.58	0.58
W = 128	0.61	**0.67**	0.55	0.65	0.58	0.58	0.58	0.59
W = 256	0.65	0.70	0.64	**0.71**	0.62	0.63	0.63	0.63
W = 512	0.69	**0.76**	0.64	**0.76**	0.67	0.69	0.69	0.70

Table(Left): Average Classification Accuracies of Different Activity Recognition Models

	Response Time (s)	Utilization CPU (%)	Consumption Power (mW)	Utilization RAM (MB)	Model Size (KB)
DFAM	**1.8**	1.7%	33.3-129.5	37	236
SVM	1.9	3.9%	33.3-188.7	43	229
DT	1.9	**0.8%**	**33.3-85.1**	36	**111**
RF	2.1	3.1%	85.1-222	68	6100
NB	**1.8**	1.3%	40.7-96.2	**20**	131
1-NN	1.9	2.1%	85.1-214.6	23	1700
2-NN	1.9	1.9%	85.1-188.7	32	1700
3-NN	1.9	2.1%	85.1-218.3	57	1700

Table(Right): Average Resource Consumption of Different Activity Recognition Models

DFAM has *comparable accuracy* and better *response times*.

The hierarchical approach towards distraction detection minimizes resource footprint in presence of mundane (simple) pedestrian activities.

Table: Resource Consumption of Hierarchical DFAM

	All	S1	S2
Response Time	1.8 s	0.6 s	0.9 s
CPU Utilization	1.7%	0.8%	1.5%
RAM Utilization	37 MB	30 MB	35 MB
Power Consumption	64.4 mW	37.8 mW	59.8 mW

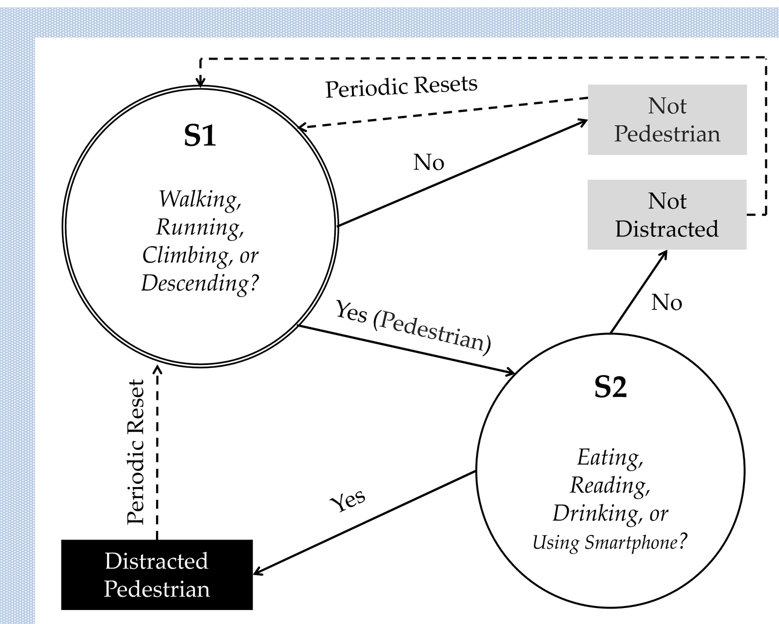


Figure: A hierarchical distraction detection framework

Plan

- Initial performance evaluation through identification and adoption of effective (and less-intrusive) user alert mechanisms.
- Extensive analysis of the framework with the help of a campus-wide test-bed.

Task Outcomes

1. N. Vinayaga-Sureshkanth, A. Maiti, M. Jadliwala, K. Crager, J. He, and H. Rathore, "*Towards a Practical Pedestrian Distraction Detection Framework using Wearables*", in IEEE WristSense, 2018 (**Best Paper Award**).
2. N. Vinayaga-Sureshkanth, A. Maiti, M. Jadliwala, K. Crager, J. He, and H. Rathore, "*A Practical Framework for Preventing Distracted Pedestrian-related Incidents using Wrist Wearables*", under Review at IEEE Access, 2018.

Ongoing and Future Work

Task 2: Further **improve** detection **response times**

Approach: Apply **Compressive Sensing (CS)** to:

- Reduce communication data size in distraction detection and cloud framework.
- Recognize distracted activities with higher block size.

Task 3: **Alert** nearby **users**

Approach: Employ **cloud** to:

- **Gather** contextual data.
- **Consolidate** hazards.
- **Distribute** knowledge.

Task objectives:

- **Real-time** service.
- Protect user **privacy.**
- **Crowd-sense** hazards.

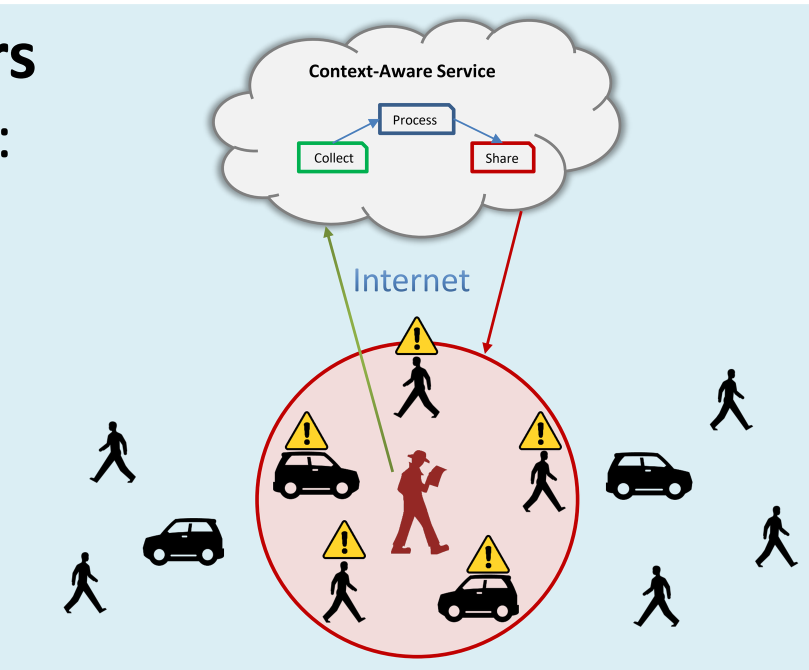
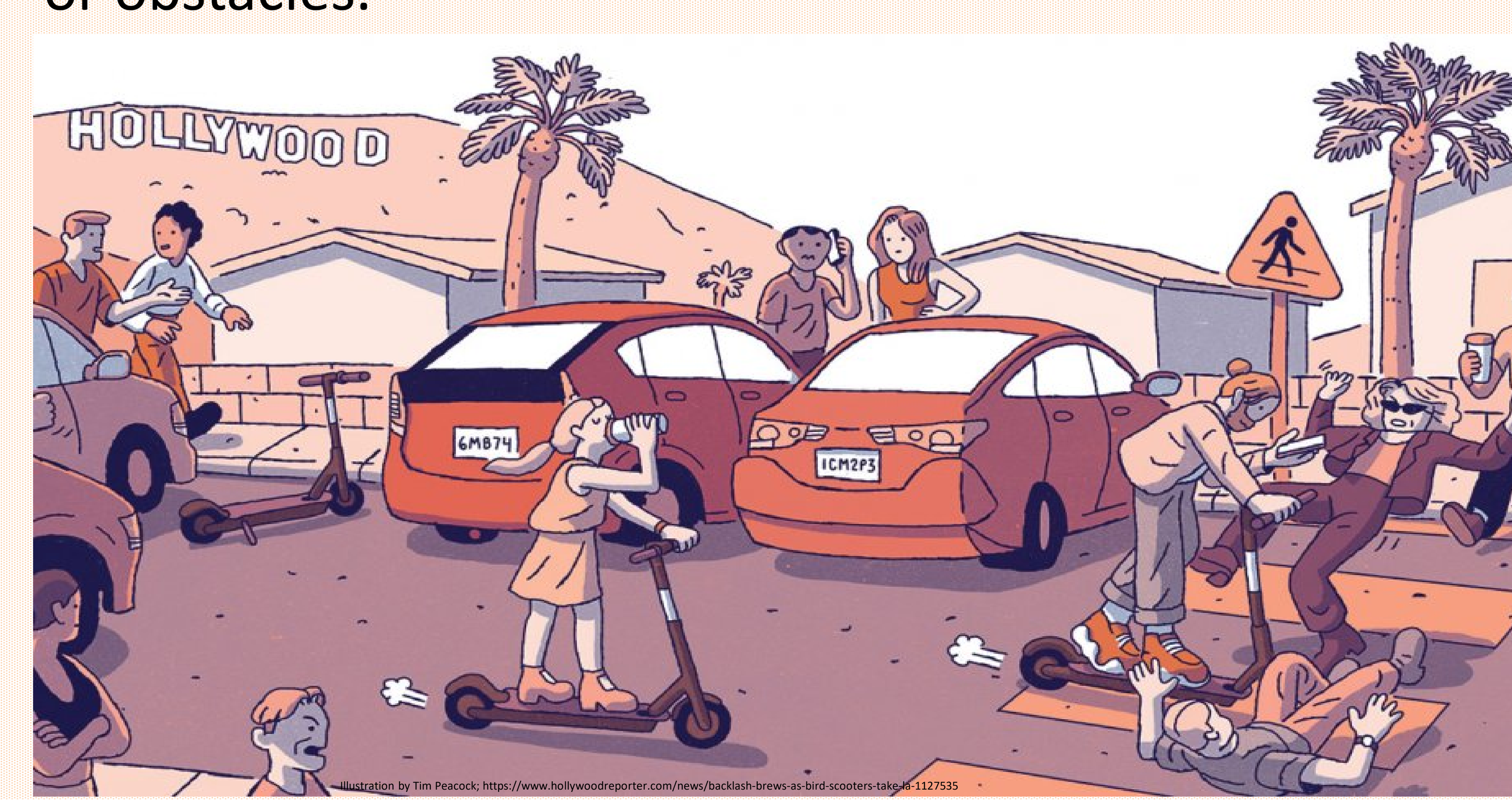


Figure: An accident prevention framework

Task 4: **Sense hazards** rather than **detect distraction**

Approach: **Ultrasonic sound** and **light sensors** to sense fast approaching hazards (e-bike riders or skateboarders) or obstacles.



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