On the Information Quality of

Energy-harvesting-based Sensing

in Motion-powered IoTs

Never Stand Still | Faculty of Engineering | Computer Science and Engineering

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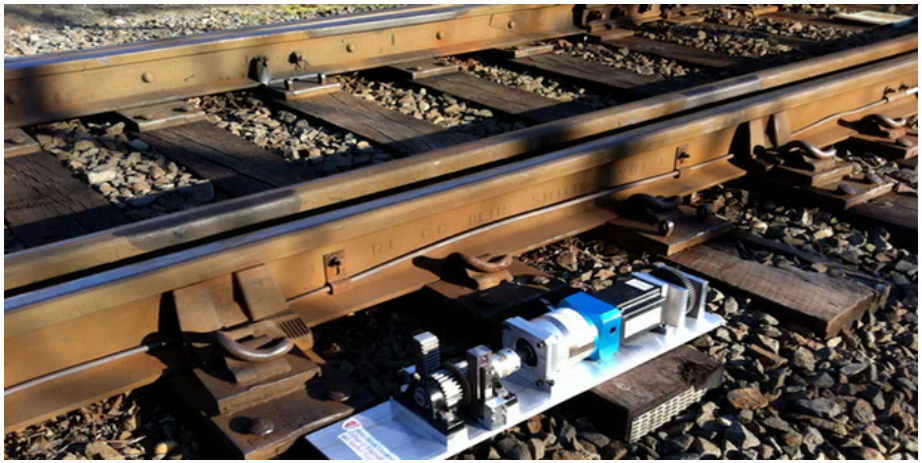
What do these IoTs have in common?

Smart Shoe from InstepNanopower

Swiss Watch about to be released

Track Monitoring IoT from ReVibe Energy



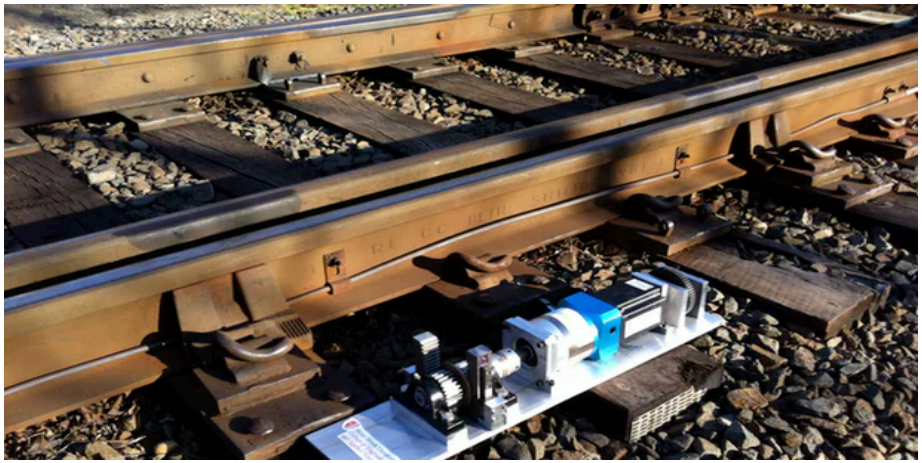
Wireless Switch from EnOcean

They are all *motion-powered* IoTs!

Smart Shoe from InstepNanopower

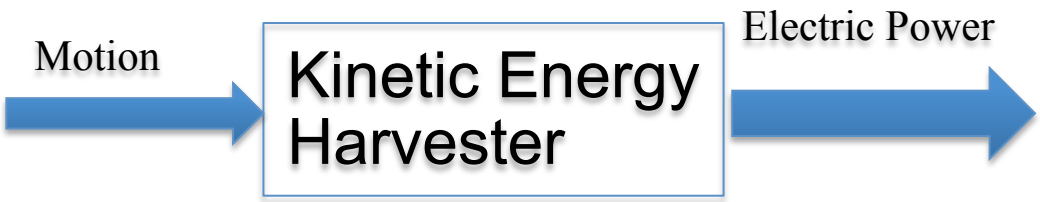
Swiss Watch about to be released

Track Monitoring IoT from ReVibe Energy



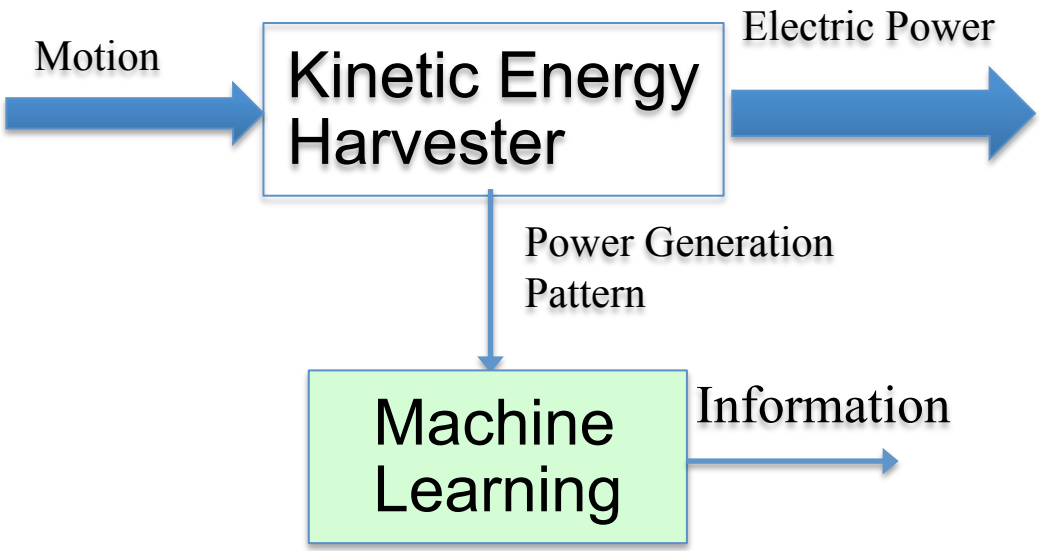
Wireless Switch from EnOcean

The essence of motion-powered IoTs



Convert mechanical to electrical energy

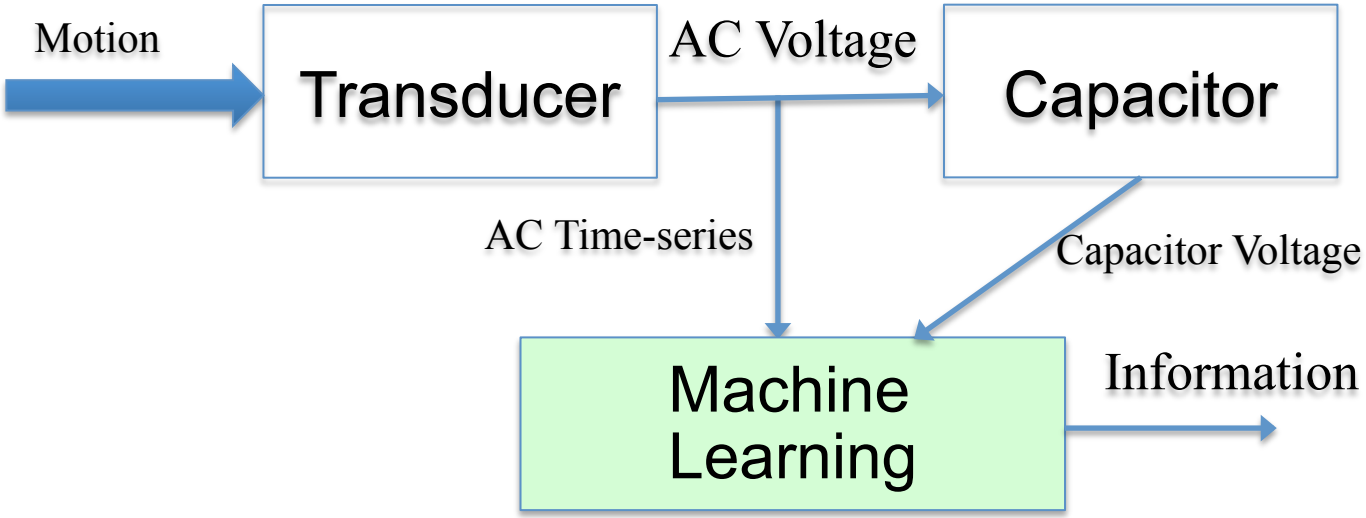
Power Data → Machine Learning → Information



Questions

- What information can be mined?
- How is the information quality?
- What factors can influence the information quality?
  - E.g., machine learning: features and classifiers
  - E.g., source of power data (time-series AC voltage vs. single-shot capacitor voltage)
  - Simultaneous sensing and energy harvesting

Types of power data for machine learning



Overview

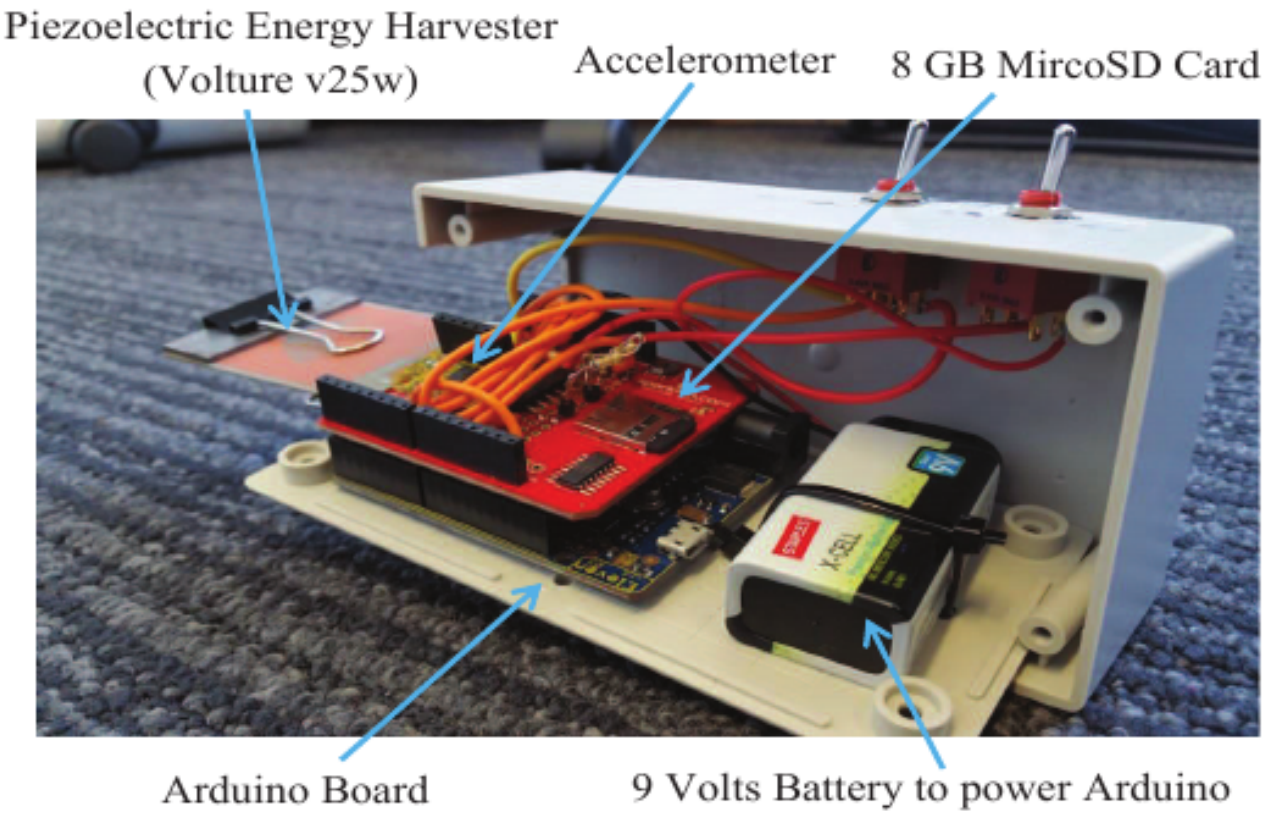
- Information quality of activity detection
  - transducer output (AC voltage) data
  - capacitor data
  - Filtering need for AC-voltage-based sensing, Case study: gait recognition
- Information quality of other type of information (if time permits)
  - Data communication
  - Voice detection
- Survey of future directions in energy harvesting and new opportunities for high quality sensing

Can we infer human activity from kinetic energy harvesting?

EXPERIMENTING WITH REAL ENERGY HARVESTERS AND HUMANS

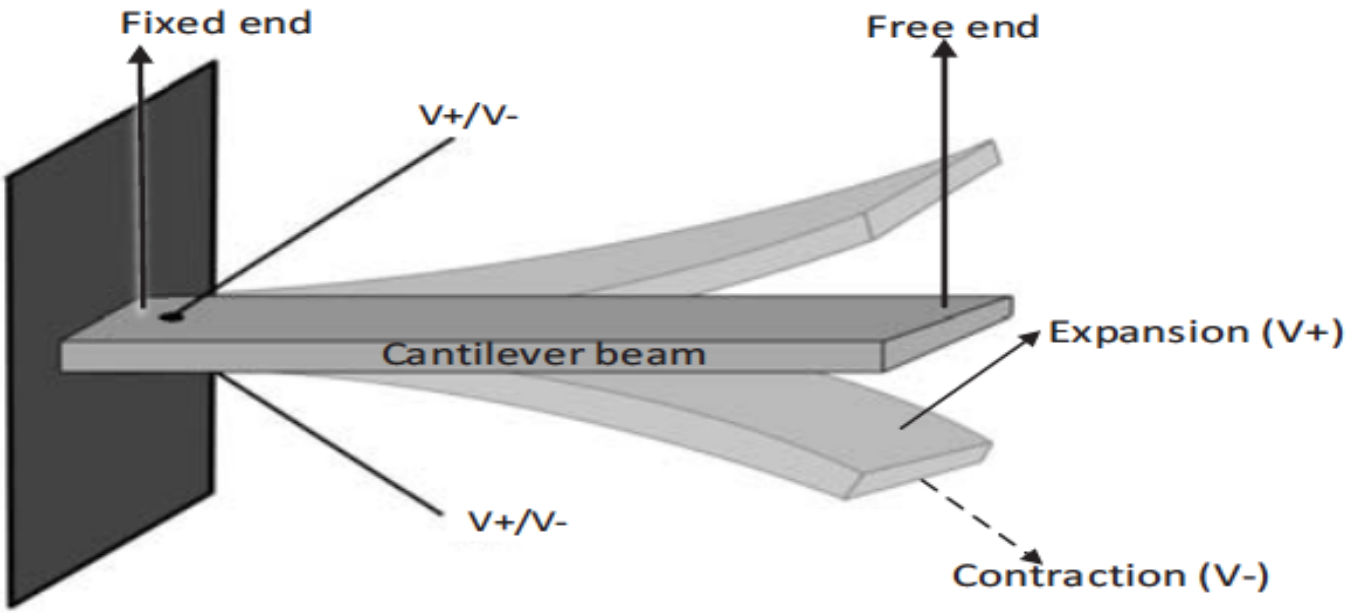
HARKE, TMC2017

KEH Data Logger (samples AC voltage values)



S. Khalifa, G. Lan, M. Hassan, A. Seneviratne, and S. K. Das, "*HARKE: Human Activity Recognition from Kinetic Energy Harvesting Data in Wearable Devices*," In IEEE Transactions on Mobile Computing (TMC), 2017.

Piezoelectric Energy Harvester (vibration-based)



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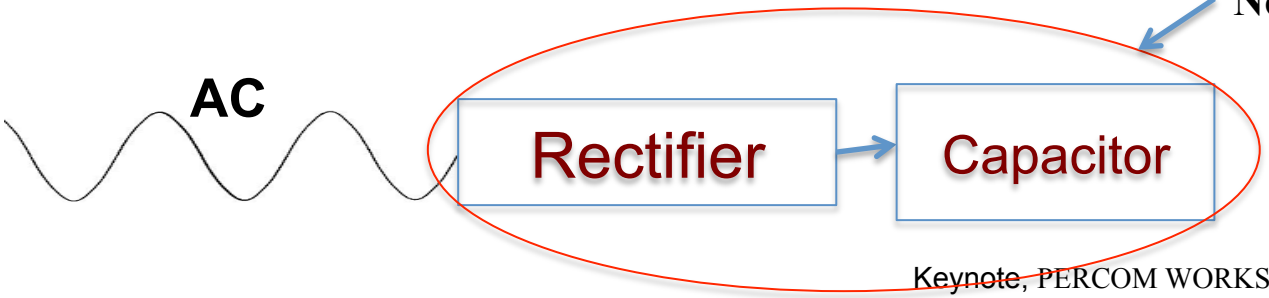
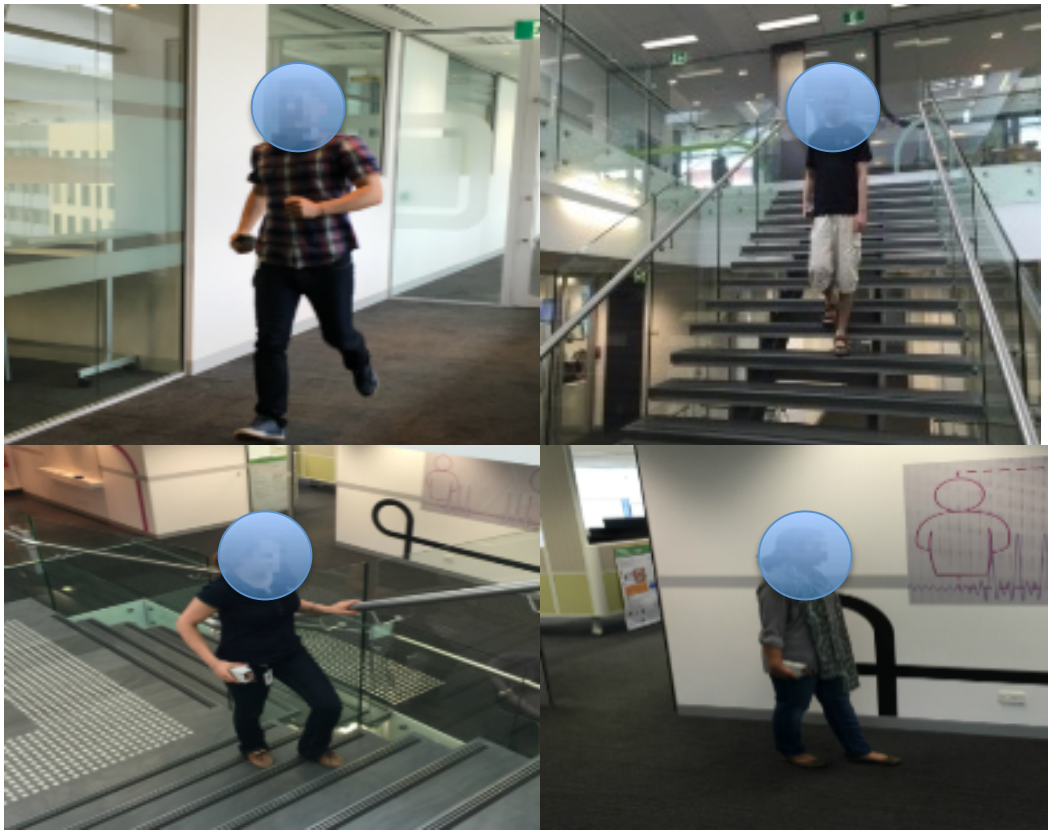
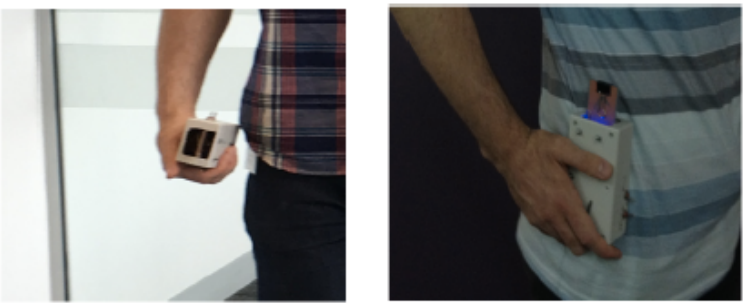
Not Implemented

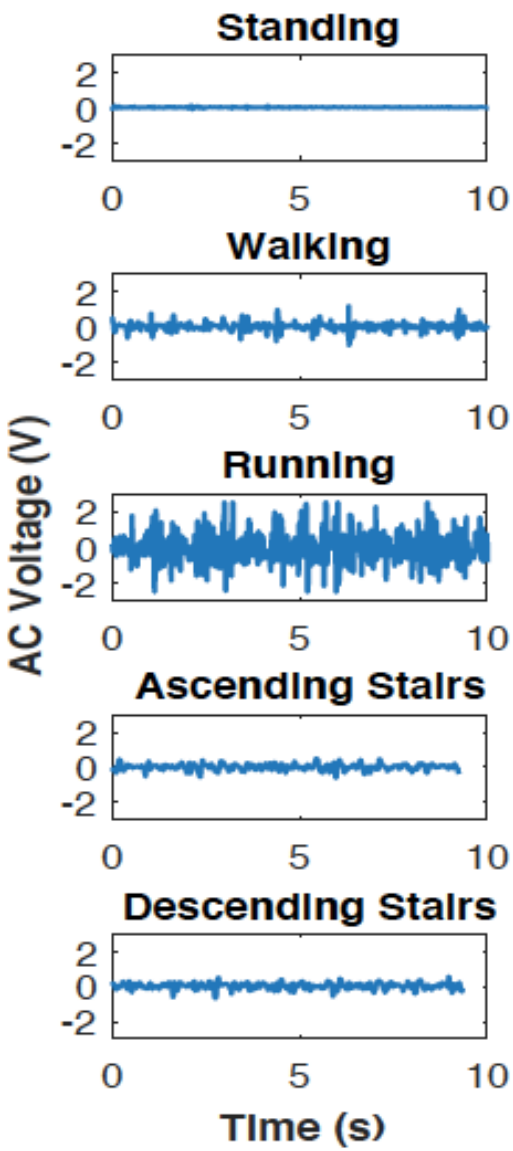


Data Collection: 10 subjects, 5 activities, 2 positions





(a) Hand (b) Waist



KEH AC Voltage Time Series

Features and classifiers matter

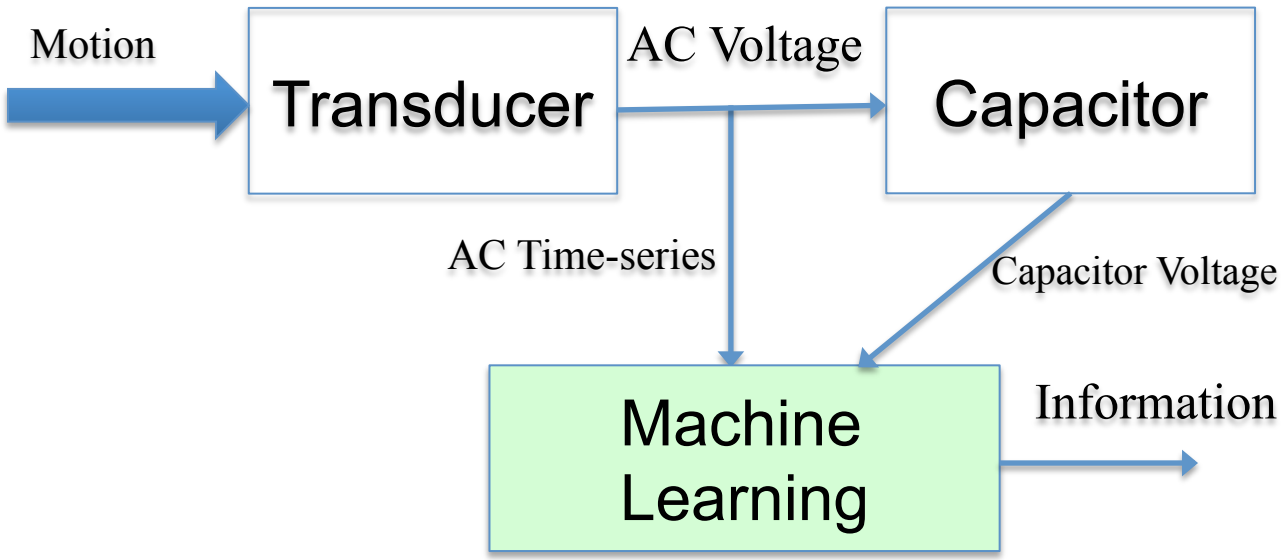
OFS: Original feature set in literature for accelerometer-based activity recognition
VFS: Vibration-based features (peak-to-peak etc.)

Classifier	with OFS		with OFS+VFS	
	Hand	Waist	Hand	Waist
NN	**70.21**	**83.51**	**80.11**	**87.36**
DT	**76.34**	79.27	79.76	80.34
SVM	72.89	75.74	72.89	79.66
NB	70.58	69.15	70.58	70.90

Activity Recognition Confusion Matrix (waist)

Activity matters: Going up and down the stairs difficult to detect, but walking/running/standing can be detected easily

		Classified as					TP Rate
		WALK	RUN	STAND	SU	SD	
Activity	WALK	48	0	0	12	4	0.75
	RUN	0	54	0	0	0	1
	STAND	0	0	73	0	0	1
	SU	17	0	1	18	3	0.46
	SD	10	0	0	6	16	0.5



Activity Detection from Capacitor Data

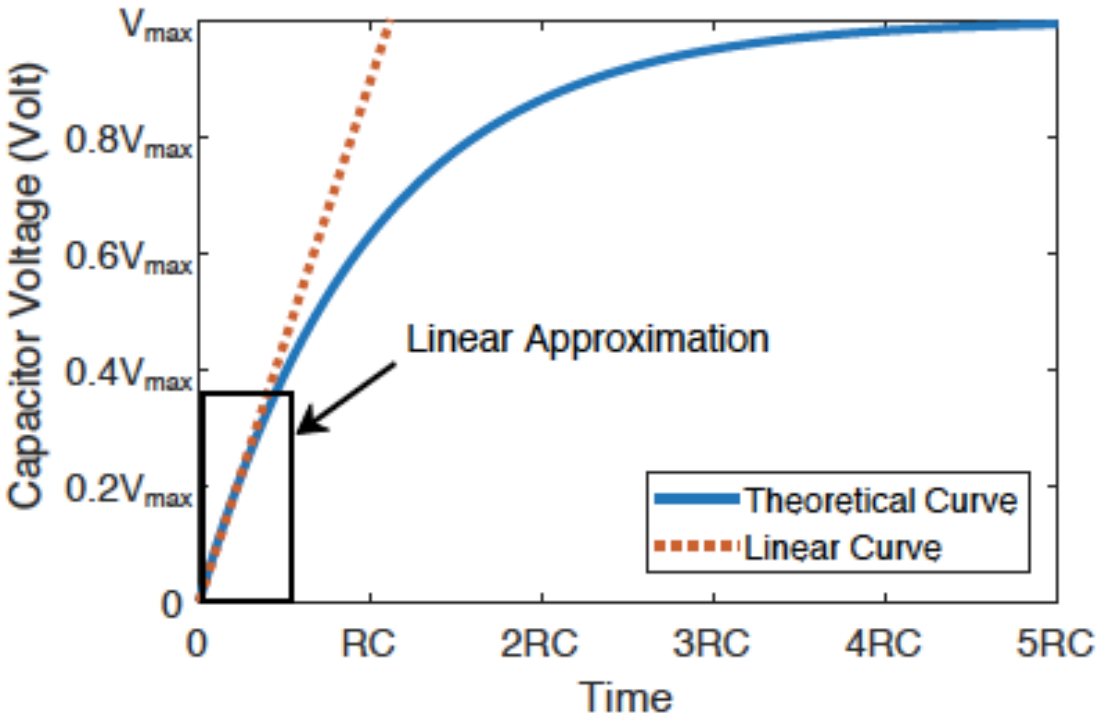
G. Lan, D. Ma, W. Xu, M. Hassan, and W. Hu, "*CapSense: Capacitor-based Activity Sensing for Kinetic Energy Harvesting Powered Wearable Devices*," In MobiQuitous'2017.

CapSense: Mobiquitous 2017

Key idea

- Different activities generate energy at different rates
- Energy generation rate can be used to detect activities
- Capacitors accumulate energy over time
- One-shot capacitor reading can classify activities (significantly more power efficient compared to AC sensing)
  - Avoid processing of time-series, computation of features, and training classifiers with large set of features

Non-linearity of capacitor voltage

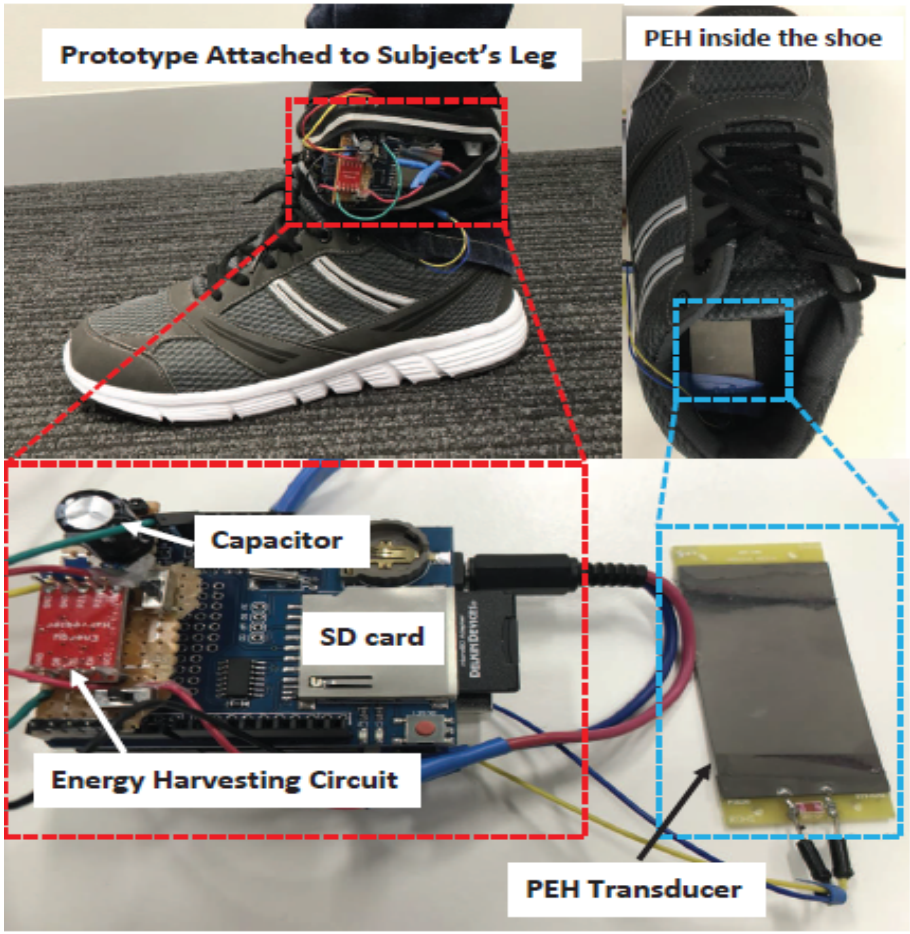


R: resistance of registor

C: capacitance of capacitor

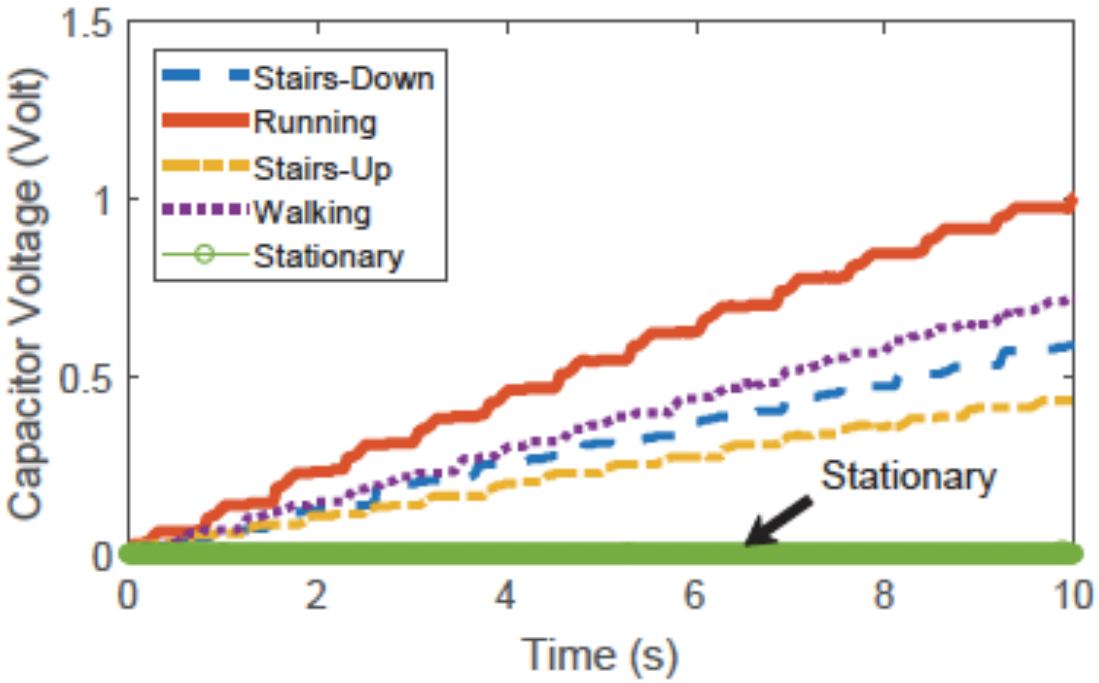
Design capacitor circuit to operate within 0.5 RC (linear)

Data Logger --- Shoe-based



Capacitor voltage data is saved in SD card for post-processing

Linear capacitor voltage curves for different activities



The longer we wait, the more distinctive the activities become

Higher information quality costs less!

No classifier bias! 7 sec. achieves 92% accuracy irrespective of the choice of classifier. Lower the sampling rate, higher the accuracy!!

Classifier	1s	2s	3s	4s	5s	6s	7s
NaiveBayes	75.89	83.39	87.84	89.51	90.59	91.92	92.68
C4.5	76.12	83.45	87.75	89.47	90.53	92.22	92.81
RandomForest	76.11	83.48	87.71	89.47	90.75	92.04	92.97
IBK	76.04	83.49	87.67	89.54	90.72	92.05	92.93
DecisionTable	75.97	83.17	87.32	89.63	90.27	91.91	92.69
BayesNets	75.96	83.05	87.62	89.55	90.12	91.57	92.29
AVG	76.02	83.33	87.65	89.51	90.65	91.95	92.72

T_C (s)

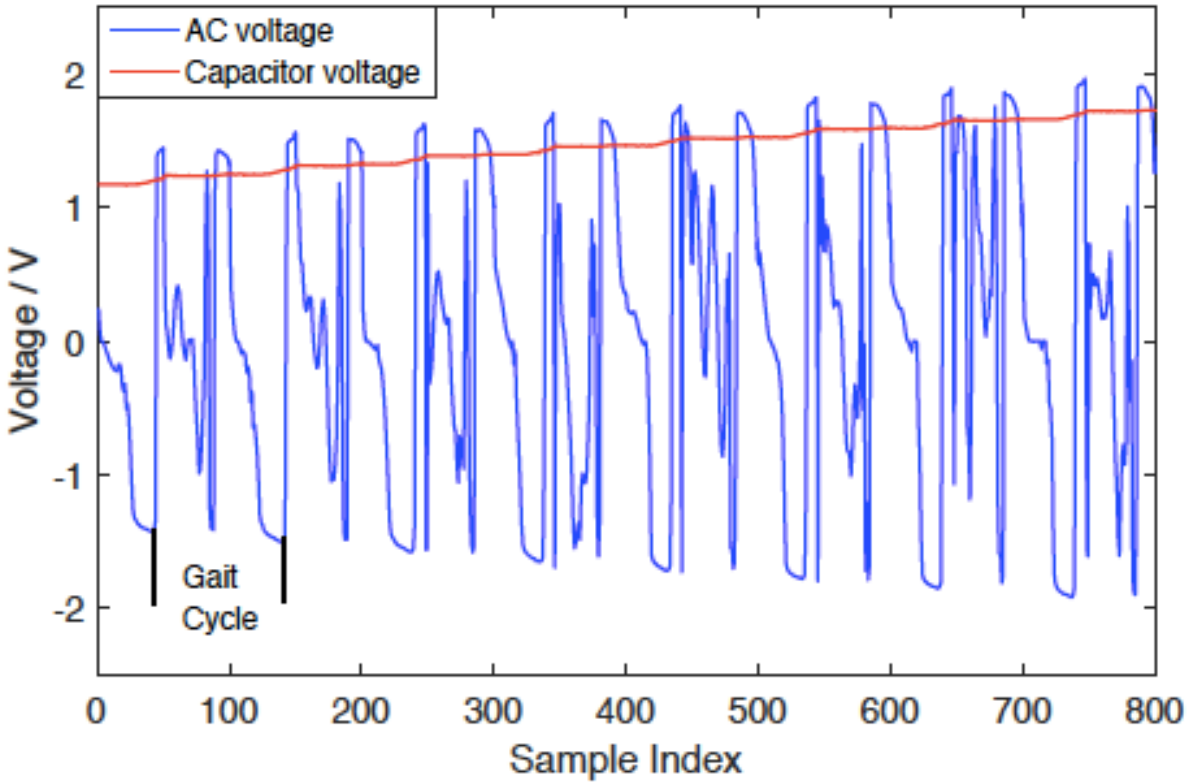
SEHS: IOTDI 2018

Impact of Capacitor Charging on the Quality of AC-voltage-based Sensing

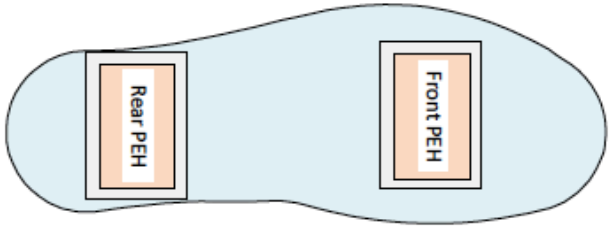
G. Lan, D. Ma, W. Xu, M. Hassan, and W. Hu, "*SEHS: Simultaneous Energy Harvesting and Sensing using Piezoelectric Energy Harvester*", in IOTDI 2018.

Capacitor voltage affects AC voltage

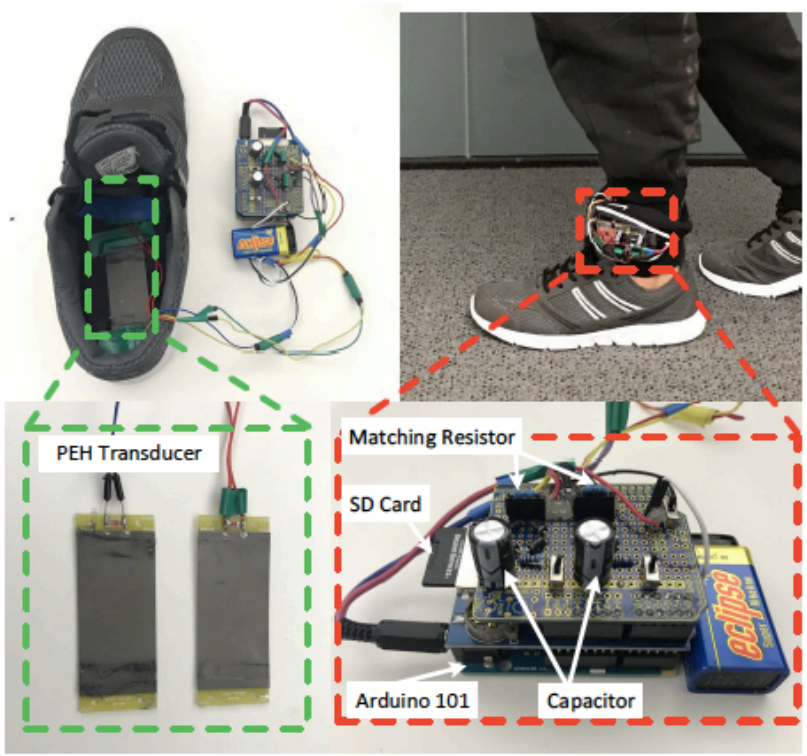
We propose AC data filter to improve information quality: case study gait detection



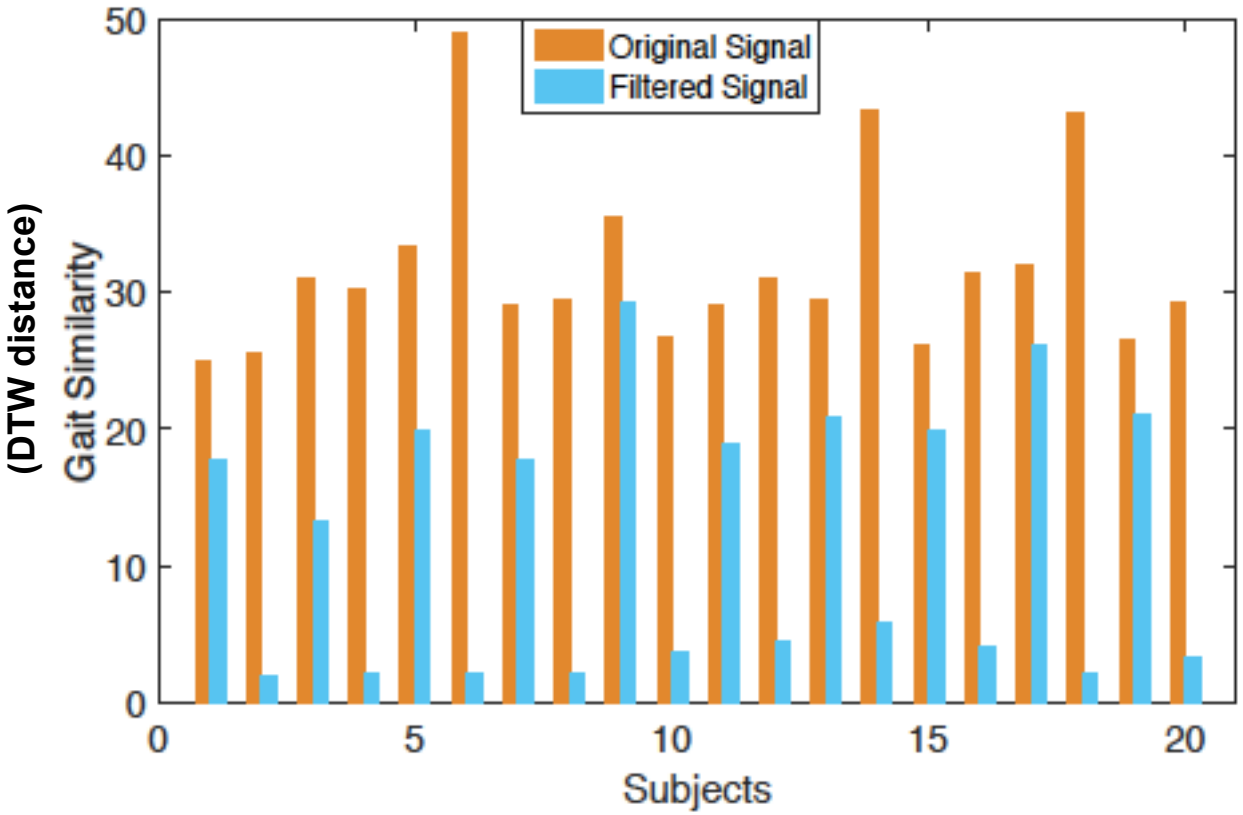
Data Logger



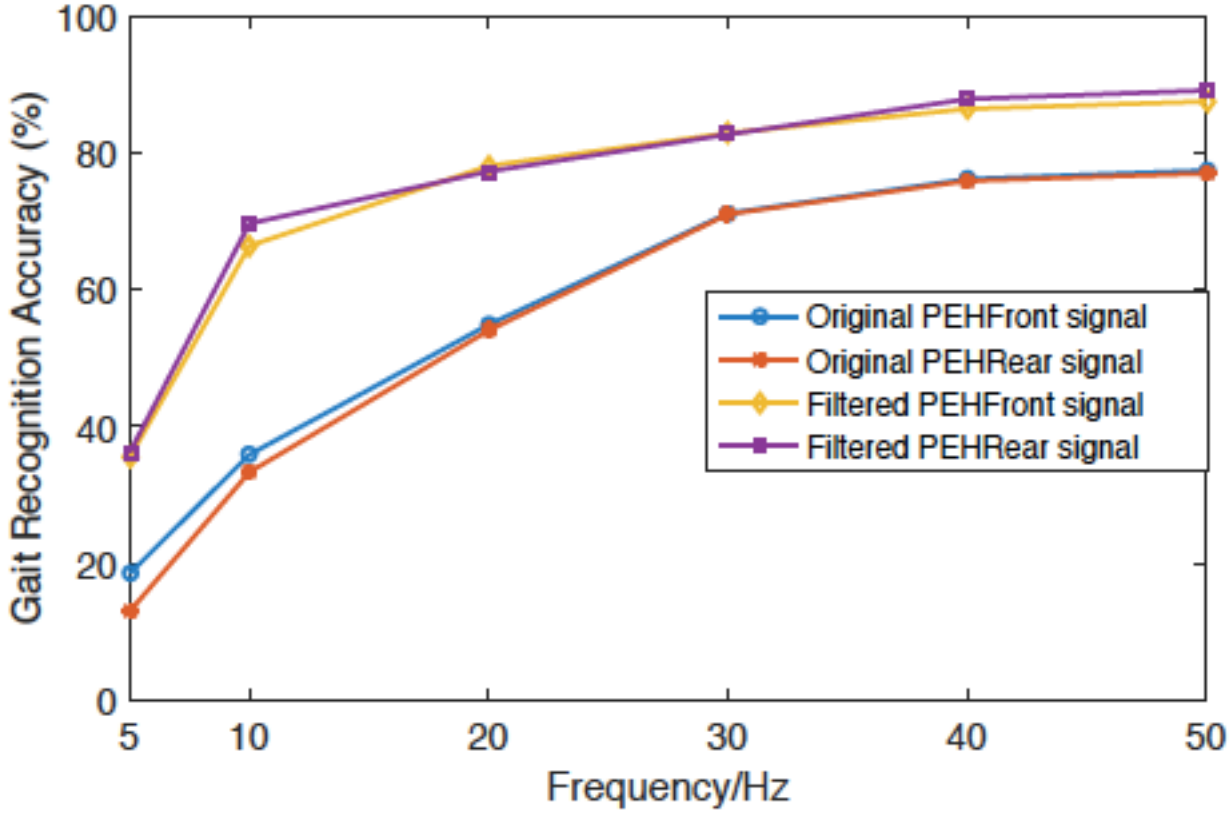
(a) Placement of PEHs on the insole



Gait Similarity



Filtering improves gait detection accuracy

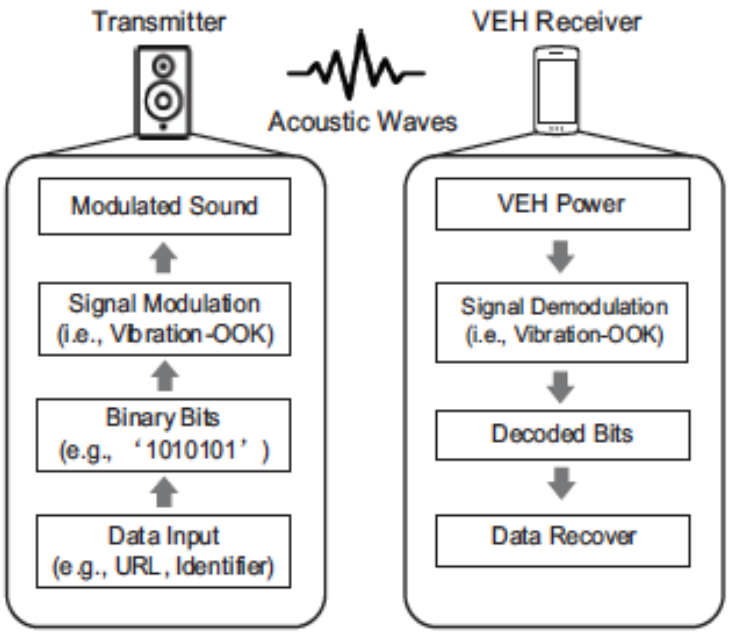


Gait recognition can be improved using Sparse Representation Classifier (SRC)

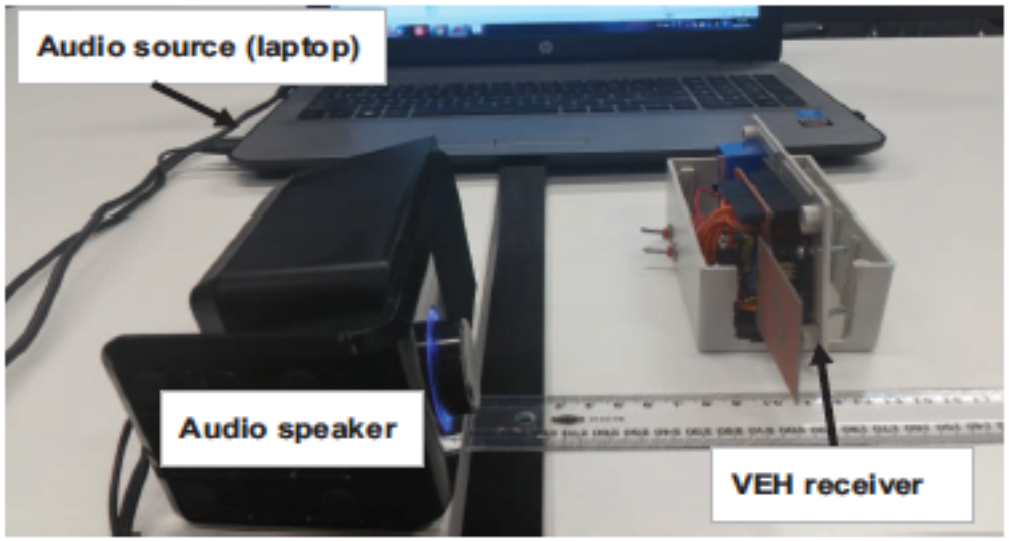
Classifier	Original signals		Filtered signals	
	PEHFront	PEHRear	PEHFront	PEHRear
KNN	54.3%	50.7%	62.9%	60.3%
SVM	66.7%	65.8%	74.4%	72.8%
SRC	76.28%	76.01%	85.56%	86.72%

Sensing from Acoustic Energy Harvesting

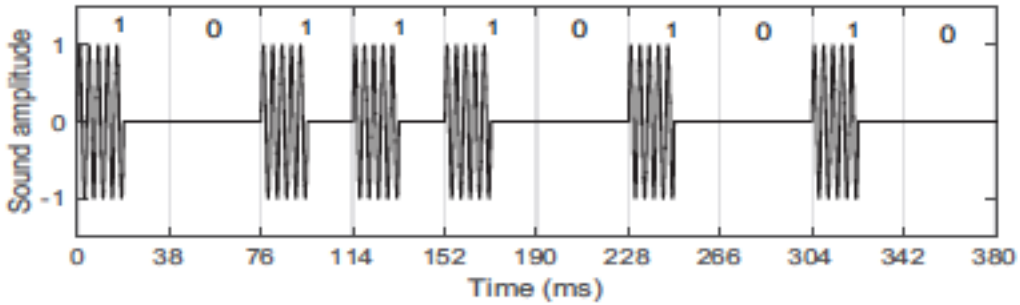
[VEHCOM: PerCom2017]



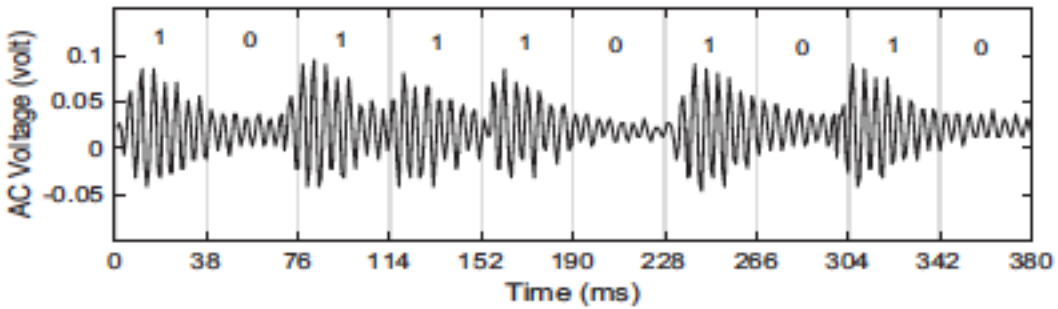
If the energy harvester can recognize known sound vibrations, it can detect communication symbols (acts as a receiver)



Impact of Transmitted Sound on Energy Harvester

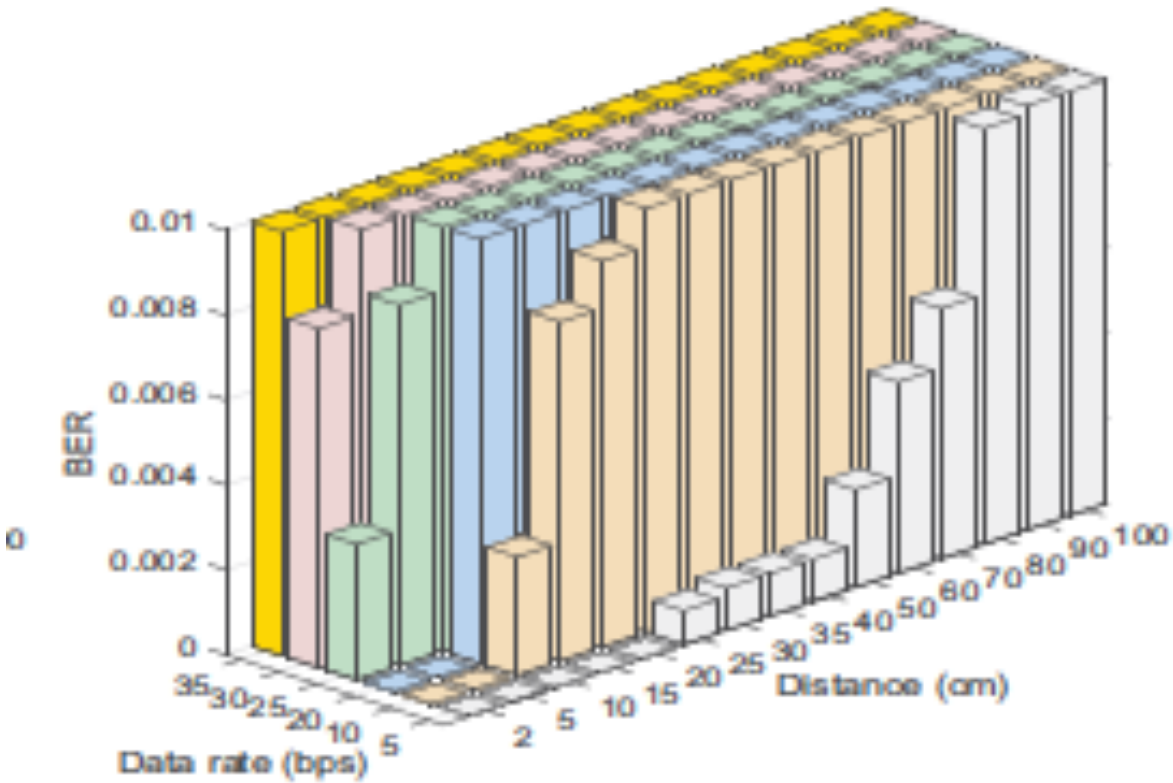


(a) Transmitted sound signal.



(b) VEH AC voltage signal.

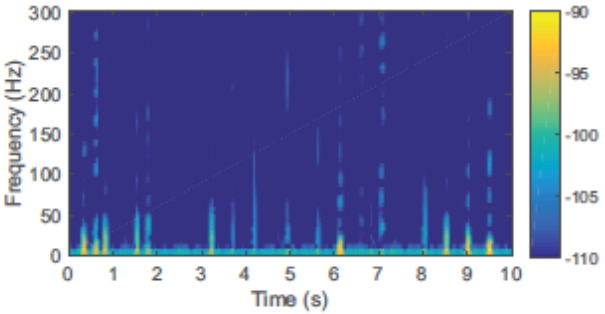
Communication Performance



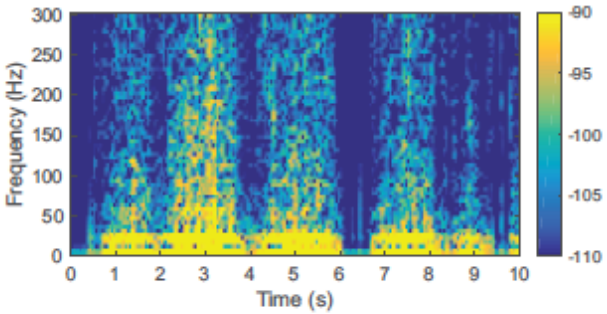
5bps at 80 cm for BER < 1% (laptop to wearable)

Natural Immunity Against Noise

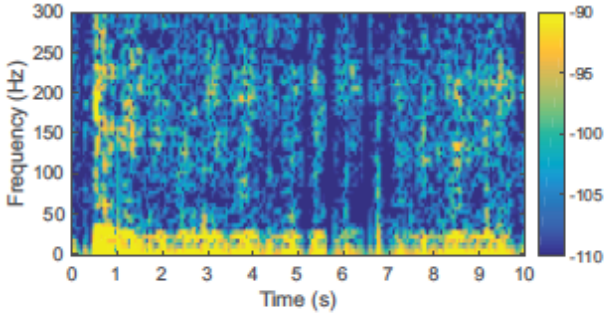
Even loud music didn't affect the communication performance



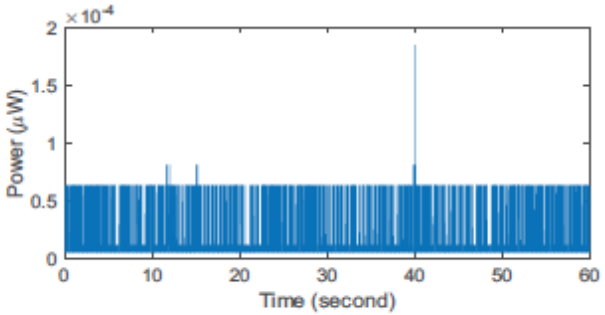
(d) VEH generated power (office)



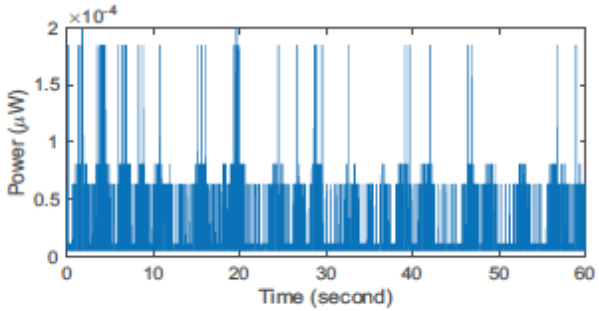
(e) VEH generated power (lounge)



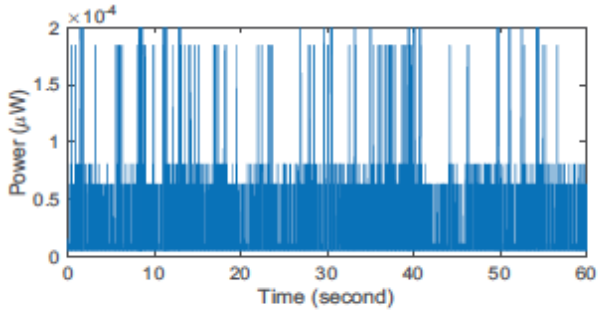
(f) VEH generated power (music)



(g) Generated noise power (office)



(h) Generated noise power (lounge)

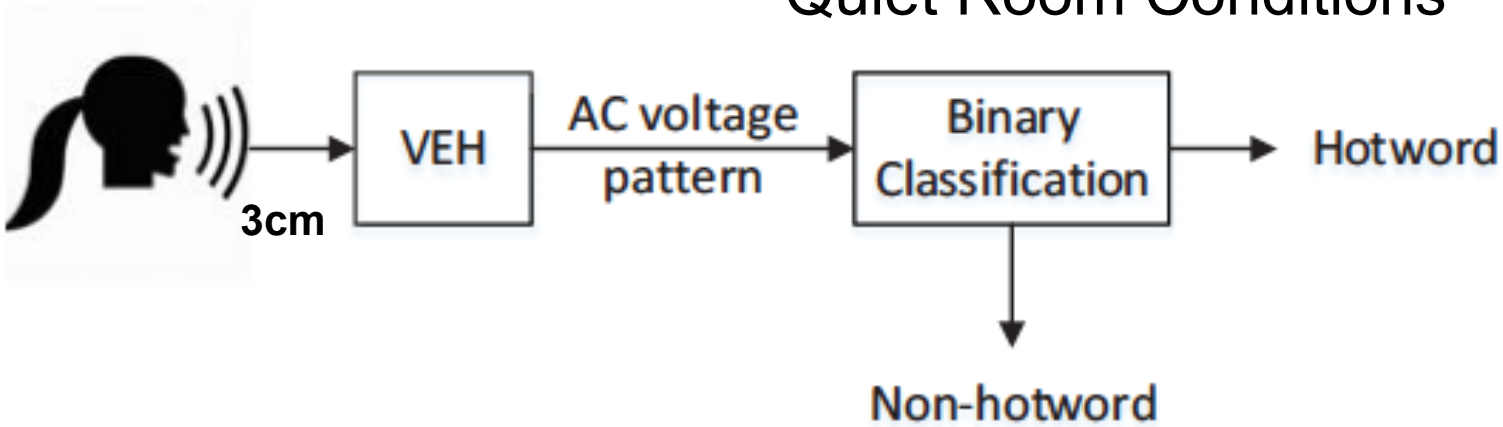


(i) Generated noise power (music)

[WOWMOM2016]

Hotword detection

Quiet Room Conditions

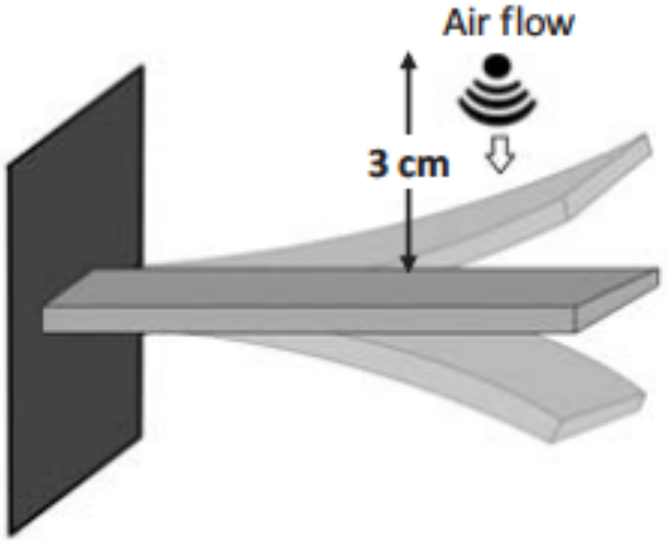


Hotword: “OK Google”

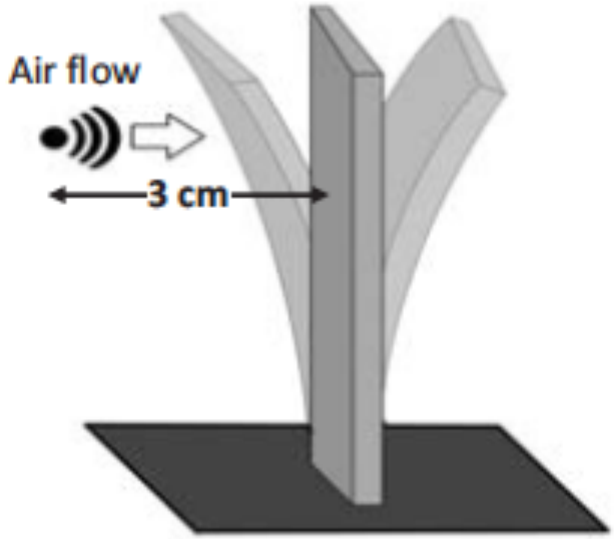
Non-hotwaods: “Good morning”, “how are you”, “fine, thank you”

8 subjects: 4 m, 4 f 60 instances (30 hotword 30 non-hotword) per subject

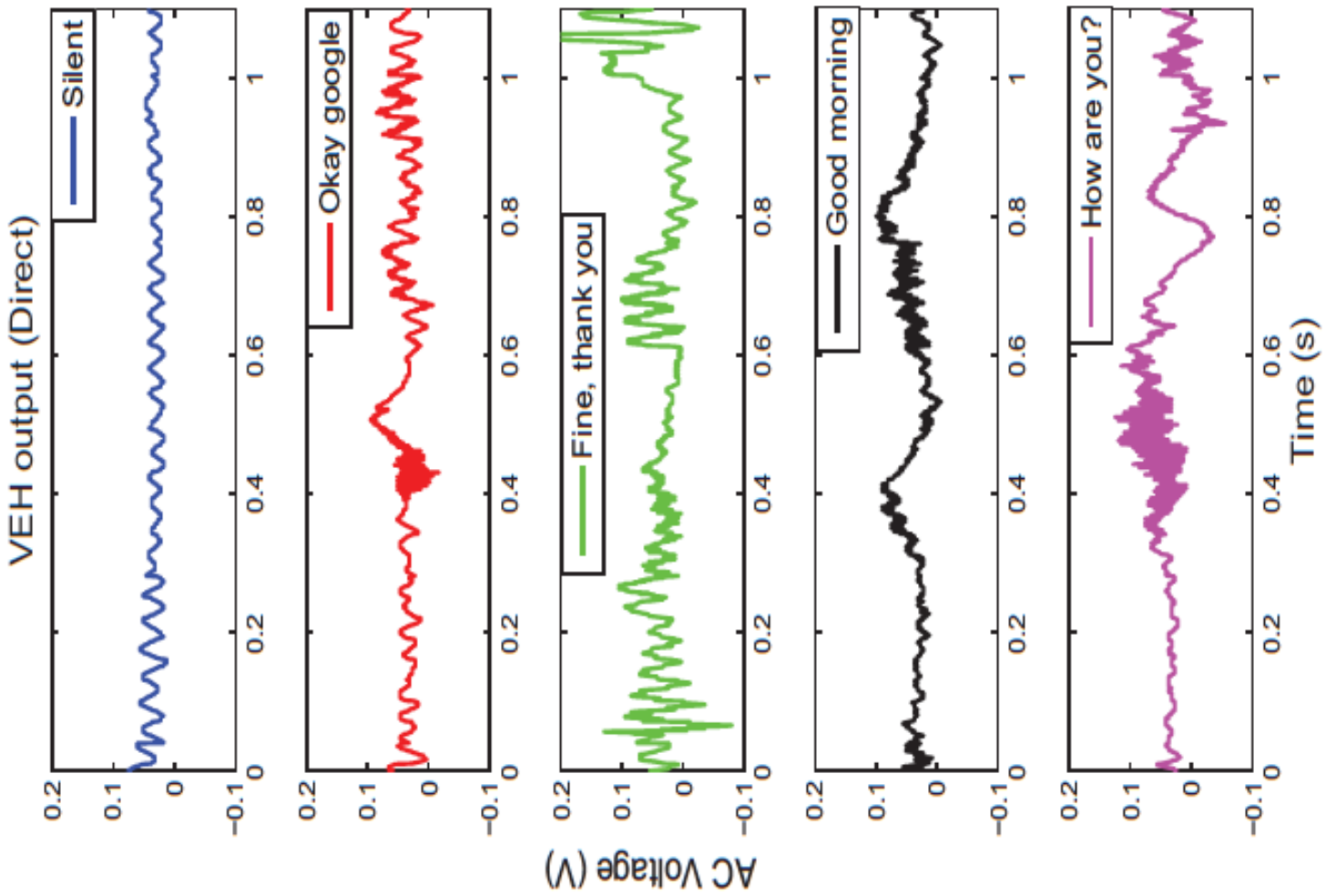
Speaker orientation



(a) Flat orientation.



(b) Vertical orientation.


VEH output (Direct)
Silent
Okay google
Fine, thank you
Good morning
How are you?
AC Voltage (V)
Time (s)
0.2
0.1
0
−0.1
0
0.2
0.4
0.6
0.8
1

Results

	Flat	Vertical
Speaker Independent	78%	62%
Speaker Dependent	85%	73%

Conclusion

- KEH data contains a lot of information about ambient context

- Information can be mined from two distinct sources within KEH
  - AC voltage [HARKE: TMC in press]
  - Capacitor voltage [CAPSENSE: MOBIQUITOUS 2017]
  - AC voltage can detect complex phenomena, such as human gait, but requires more intense processing; simpler information can be obtained from capacitor more efficiently

- Capacitor voltage interferes with AC voltage [SEHS: IOTDI 2018]
  - Need for AC voltage data filtering

Future Directions

① Advanced machine learning → increase range and quality of information

② Advanced energy harvesters → increase both power and information content

- Multi-axial, array, nanotechnology, broadband, hybrid (more details in IEEE Computer 2018)

References

1. HARKE: Human Activity Recognition from Kinetic Energy Harvesting Data in Wearable Devices, In Press. IEEE Transactions on Mobile Computing.
2. Kinetic-Powered Wearable IoT for Healthcare: Challenges and Opportunities, In Press. IEEE Computer.
3. HiddenCode: Hidden Acoustic Signal Capture with Vibration Energy Harvesting, PERCOM 2018.
4. SEHS: Simultaneous Energy Harvesting and Sensing using Piezoelectric Energy Harvester, IOTDI 2018.
5. KEH-Gait: Towards a Mobile Healthcare User Authentication System by Kinetic Energy Harvesting, NDSS 2017.
6. VEH-COM: Demodulating Vibration Energy Harvesting for Short-Range Communications, PERCOM 2017.
7. CapSense: Capacitor-based Activity Sensing for Kinetic Energy Harvesting Powered Wearable Devices, MobiQuitous 2017.
8. Feasibility and Accuracy of Hotword Detection using Vibration Energy Harvester, WOWMOM 2016.

Questions?

Power Measurements (KEH vs accelerometer)

TI Sensor Tag

96%

power saving