Personal Sensing
Indoor

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Papers

Yiran Zhao, Shuochao Yao, Shen Li, Shaohan Hu, Huajie Shao, Tarek Abdelzaher, "VibeBin: A Vibration-Based Waste Bin Level Detection System," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), also presented at Ubicomp, Maui, HI, September 2017.

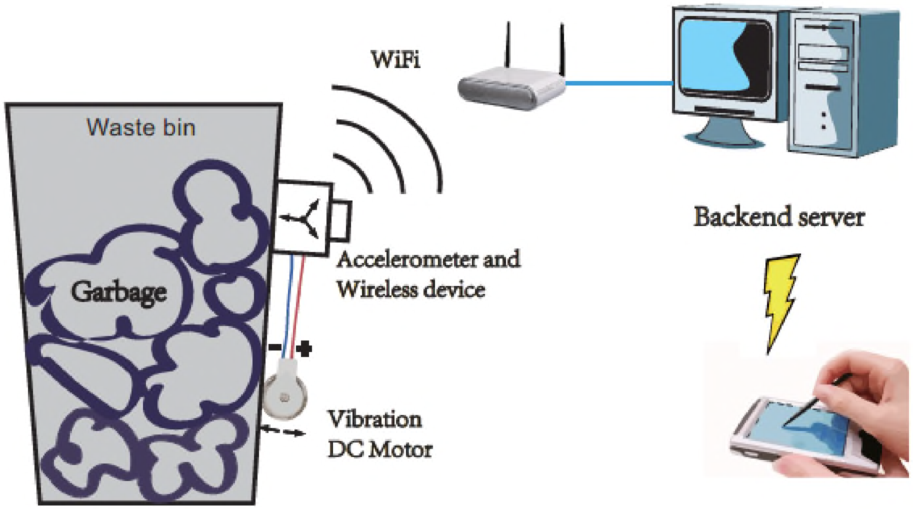
Anh Nguyen, Raghda Alqurashi, Zohreh Raghebi, Farnoush Banaei-kashani, Ann C. Halbower, and Tam Vu, "A Lightweight and Inexpensive In-ear Sensing System For Automatic Whole-night Sleep Stage Monitoring," ACM SenSys, November 2016.

Joshua Adkins and Prabal Dutta, "Monoxalyze: Verifying Smoking Cessation with a Keychain-sized Carbon Monoxide Breathalyzer," ACM SenSys, November 2016.

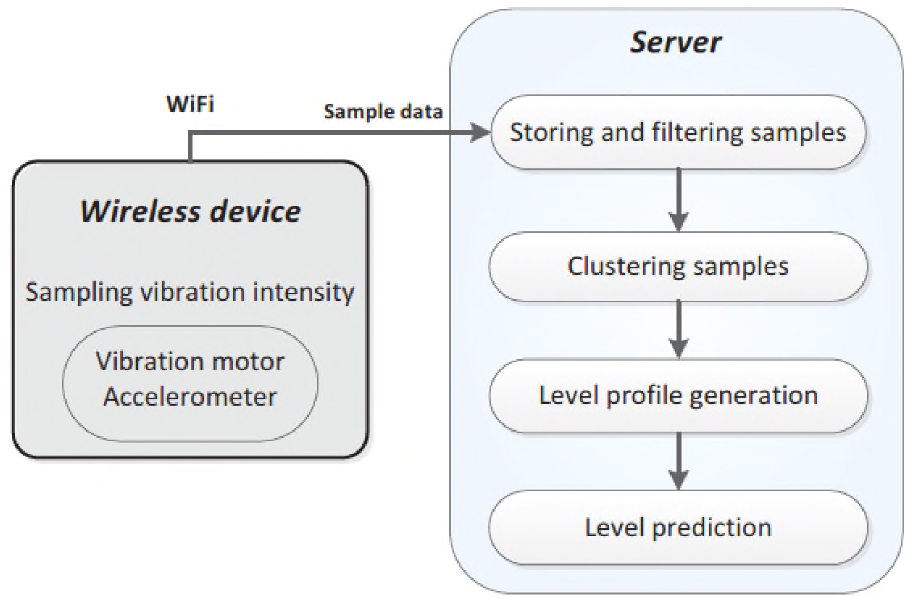
Hua Huang and Shan Lin, "Toothbrushing Monitoring using Wrist Watch," ACM SenSys, November 2016.

Valerie Galluzzi, Ted Herman, and Philip Polgreen, "Hand Hygiene Duration and Technique Recognition Using Wrist-worn Sensors," IEEE/ACM IPSN, April 2015.

VibeBin



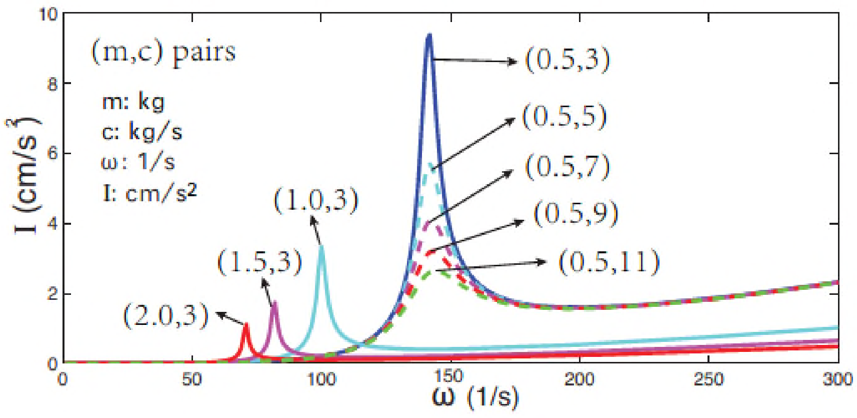
WiFi
Waste bin
Garbage
Accelerometer and
Wireless device
Vibration
DC Motor
Backend server

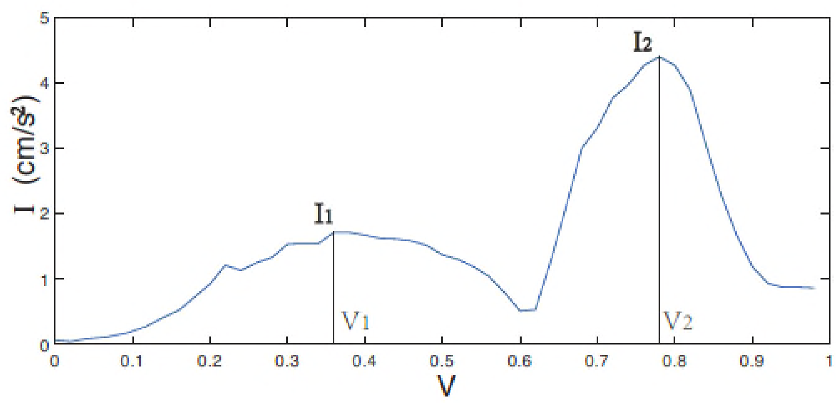


WiFi
Sample data
Wireless device
Sampling vibration intensity
Vibration motor
Accelerometer
Server
Storing and filtering samples
Clustering samples
Level profile generation
Level prediction

The Vibration Signature

- Vibration intensity depends on frequency in a manner that depends on fill level





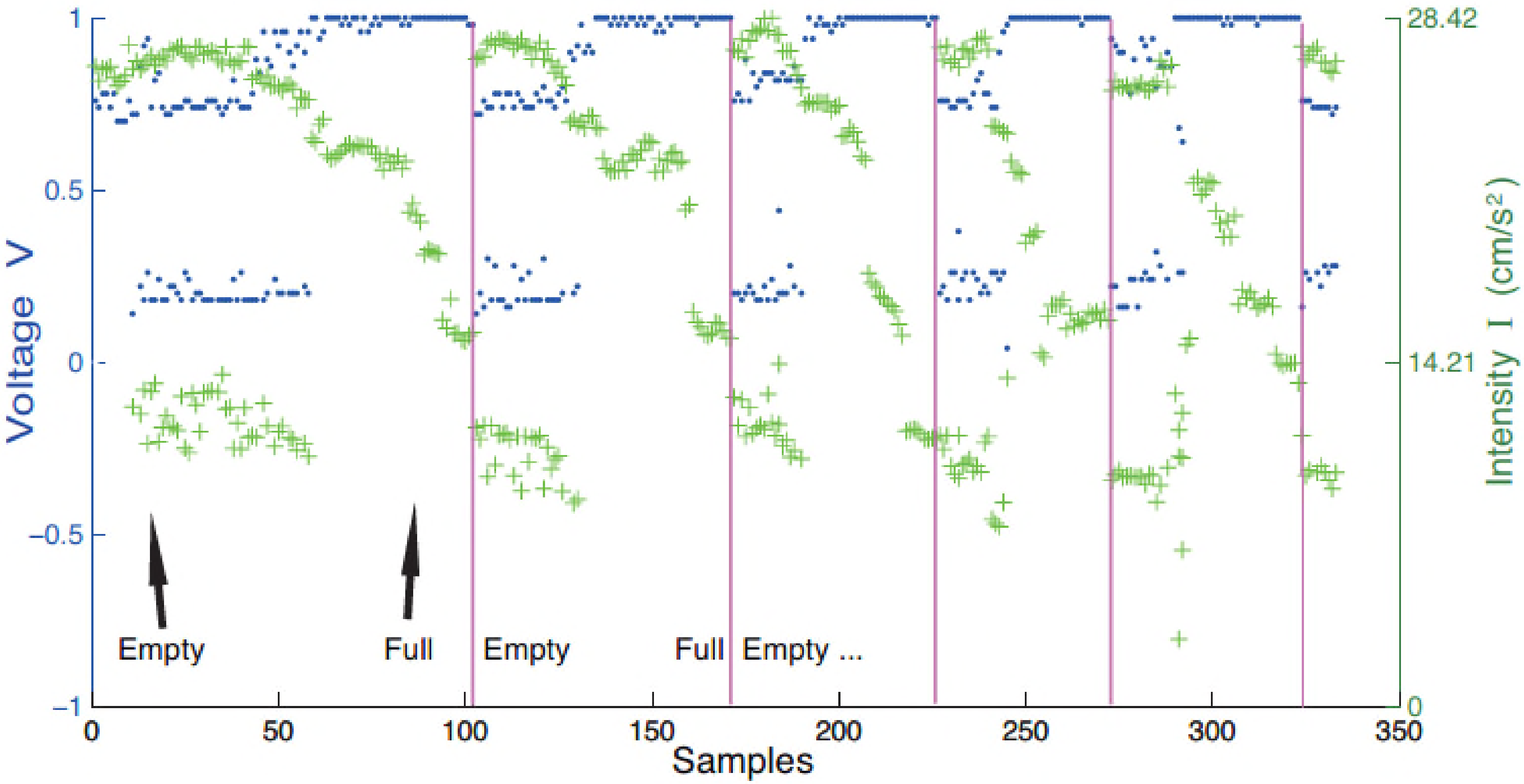
Hardware

- Does not require line of sight and does not depend on weight



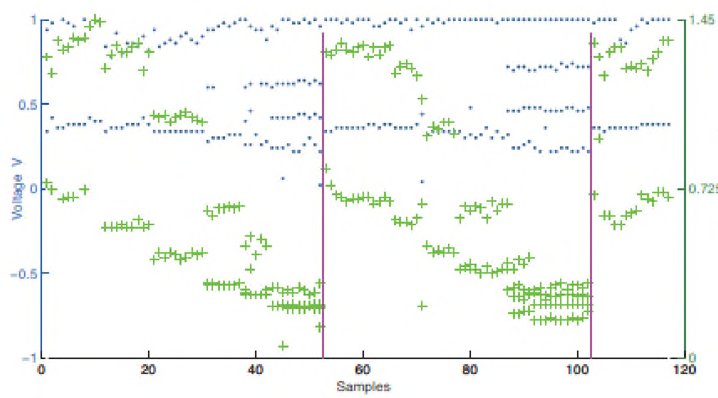

Learning and Self-calibration

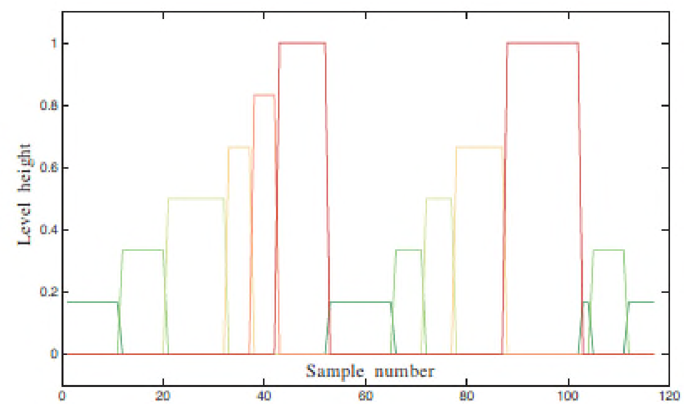
- Automatically learns when bin is full



Learning and Self-calibration

- Automatically learns when bin is full
- Automatically computes vibration features at empty, half full and full levels





Misclassifications

- Confusion matrix

(a) Bin1

110	0	0
3	82	17
1	8	97

(b) Bin2

109	2	0
0	99	10
0	0	105

(c) Bin3

108	0	0
5	85	8
0	4	102

(d) Bin4

103	0	0
31	71	0
0	4	97

(e) Bin5

93	10	0
3	99	0
0	19	82

(f) Bin6

99	0	0
1	66	31
0	0	105

(g) Bin7

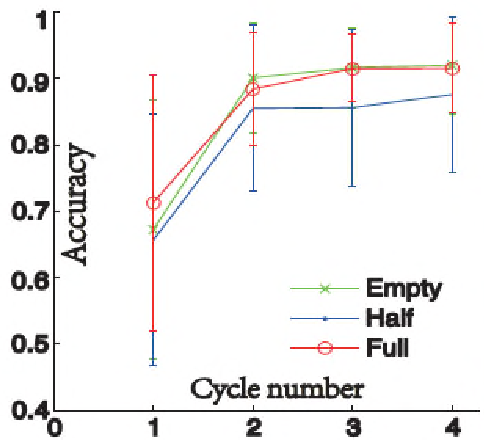
108	0	1
6	80	14
1	8	97

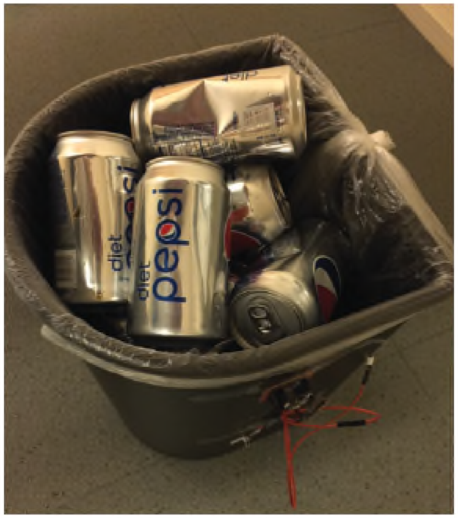
(h) Bin8

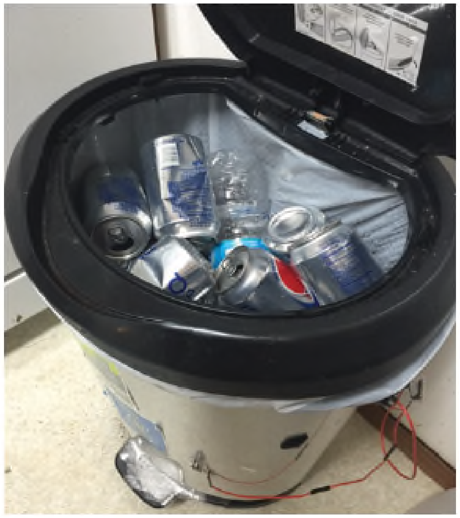
118	0	0
0	91	19
0	11	89

Learning over Time

- Accuracy improves over time

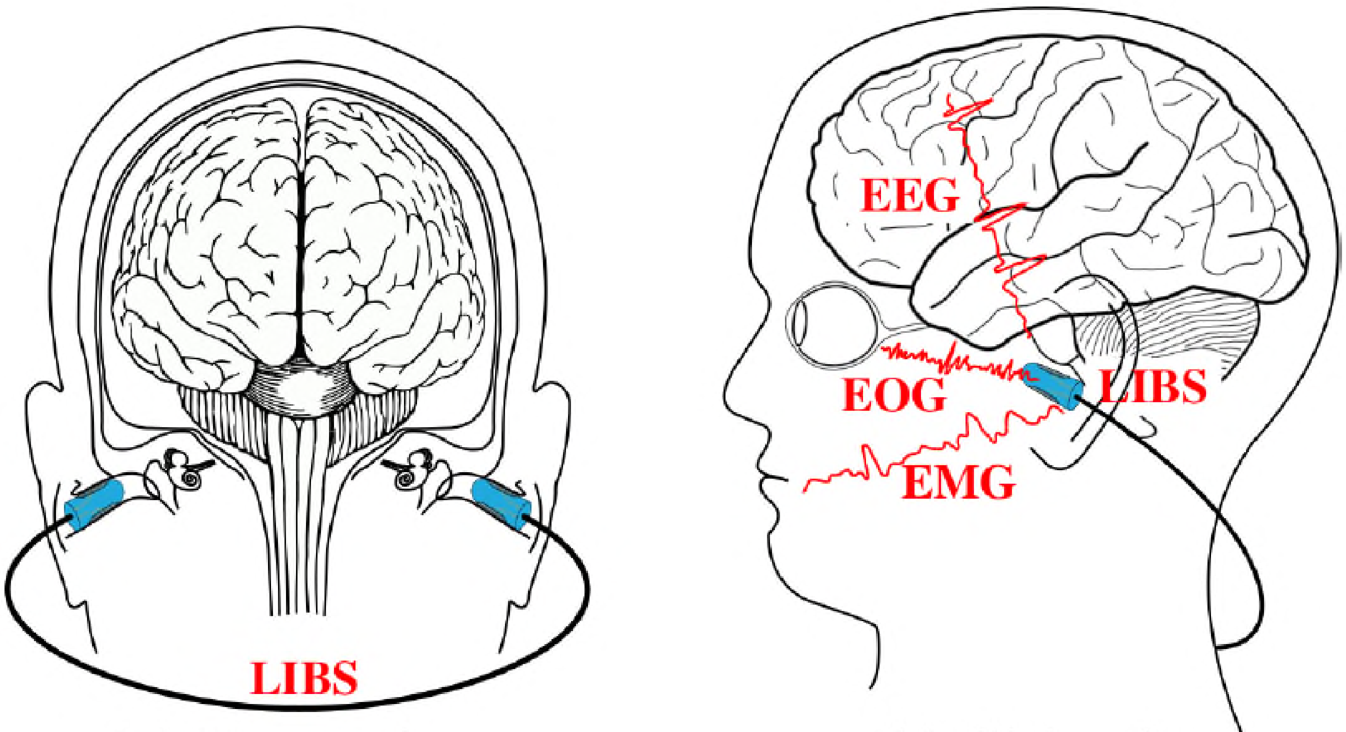






In Ear Sleep Stage Detection

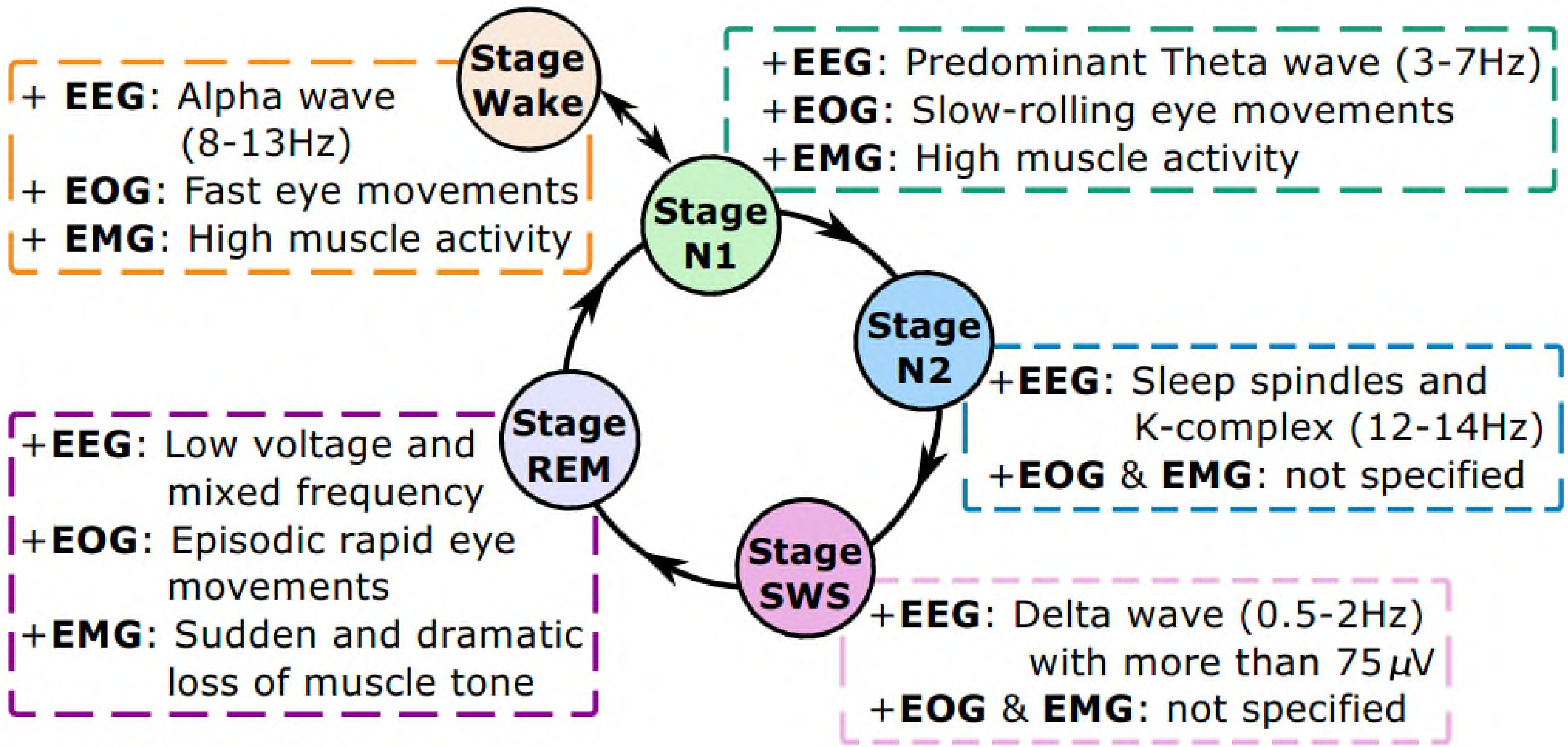
- Three signals are used to determine sleep stage



(a) Front view (b) Side view

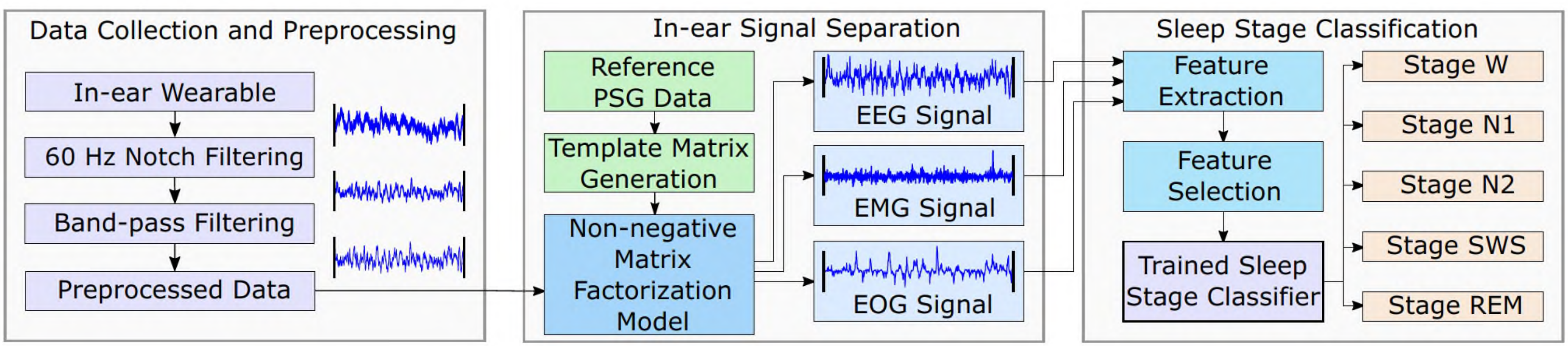
Sleep Stages

- Determined by EEG, eye activity, and skin muscle tone/activity



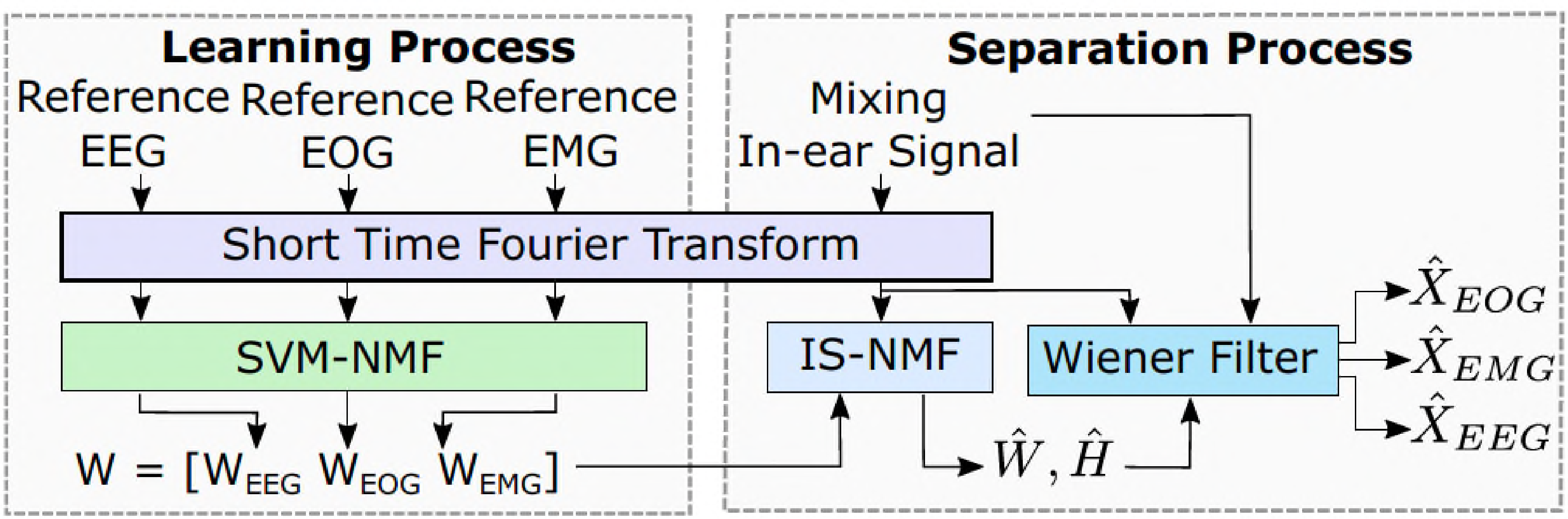
System Architecture

- Collection,
- Separation, and
- Activity detection



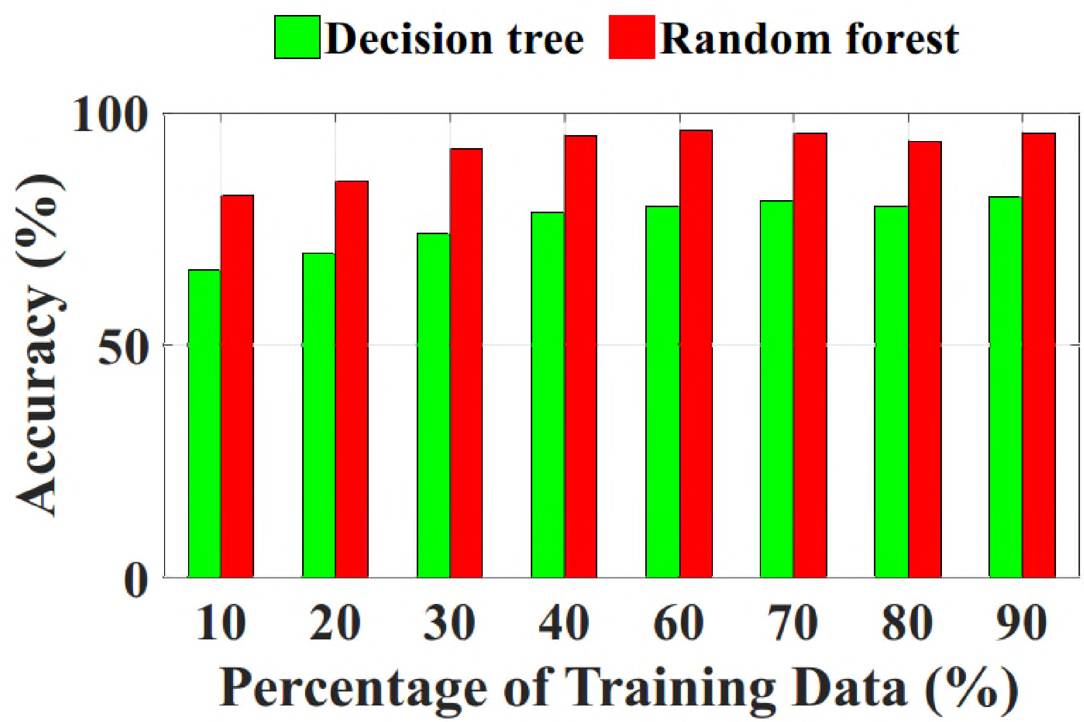
Signal Separation

- Non-negative matrix factorization



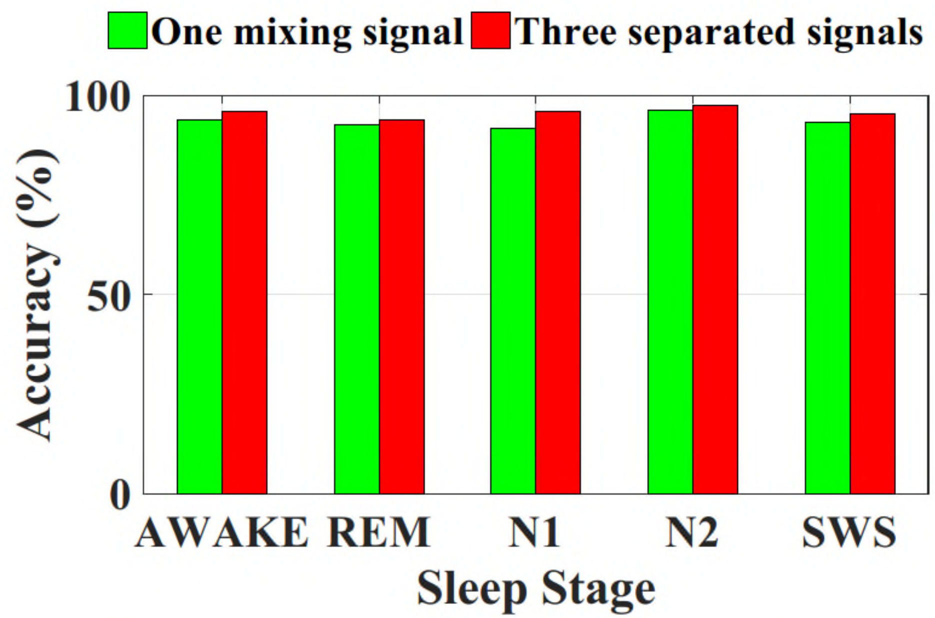
Accuracy

- Classification accuracy

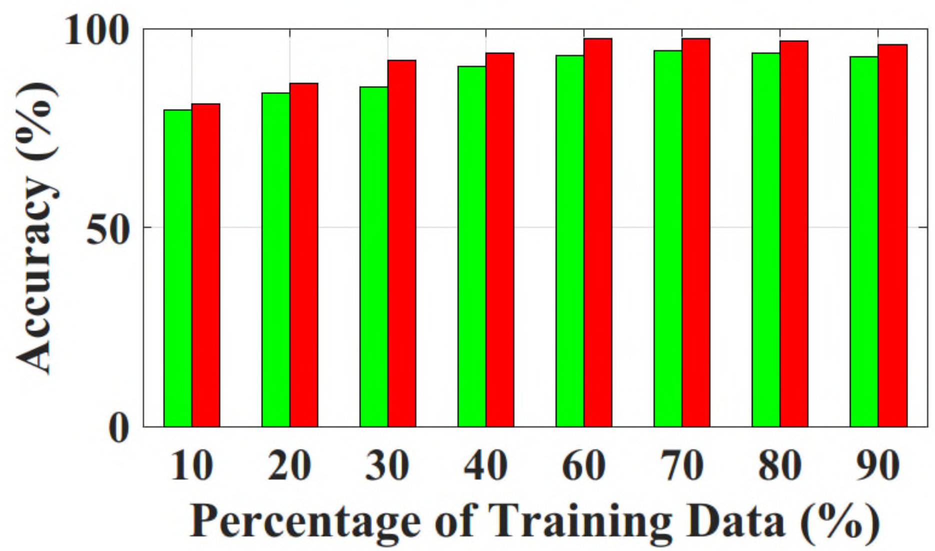


Accuracy

- Per-stage accuracy

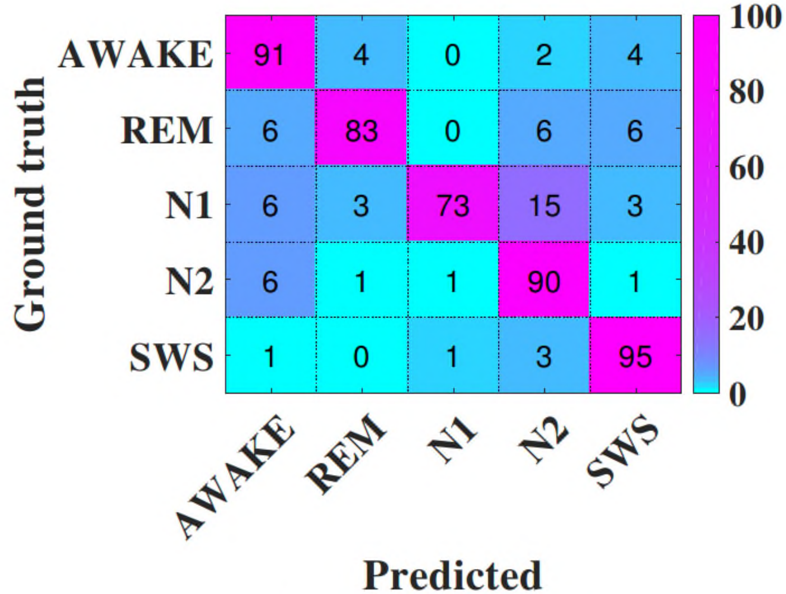


- Dependence on amount of training



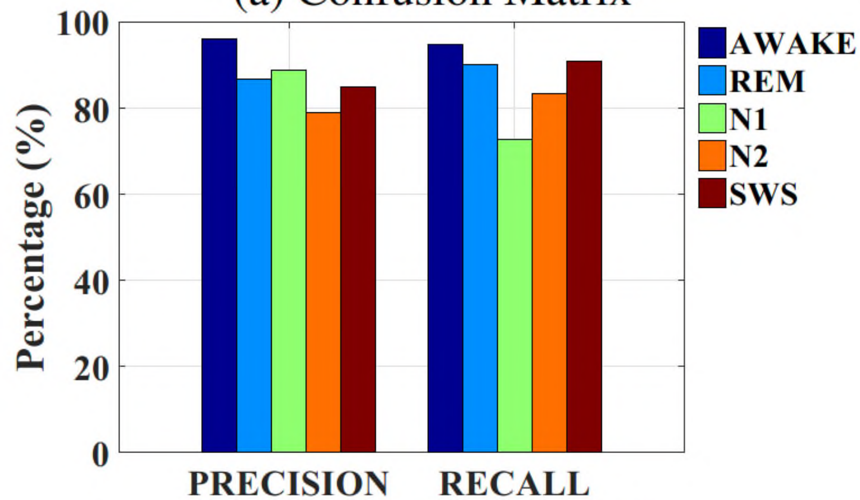
Confusion, Precision, and Recall

- Confusion matrix



(a) Confusion Matrix

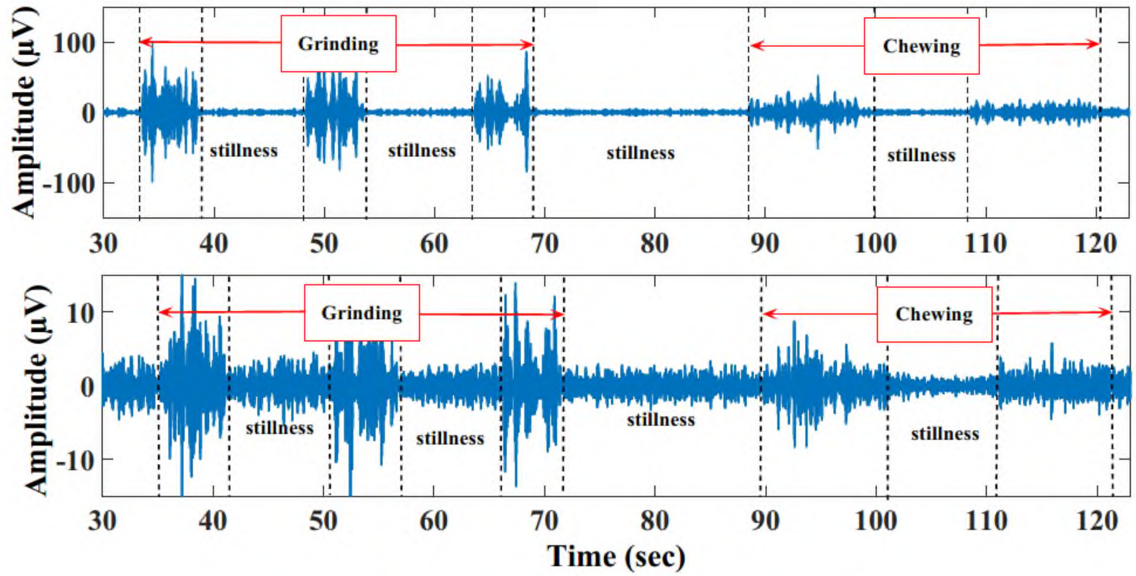
- Precision and recall



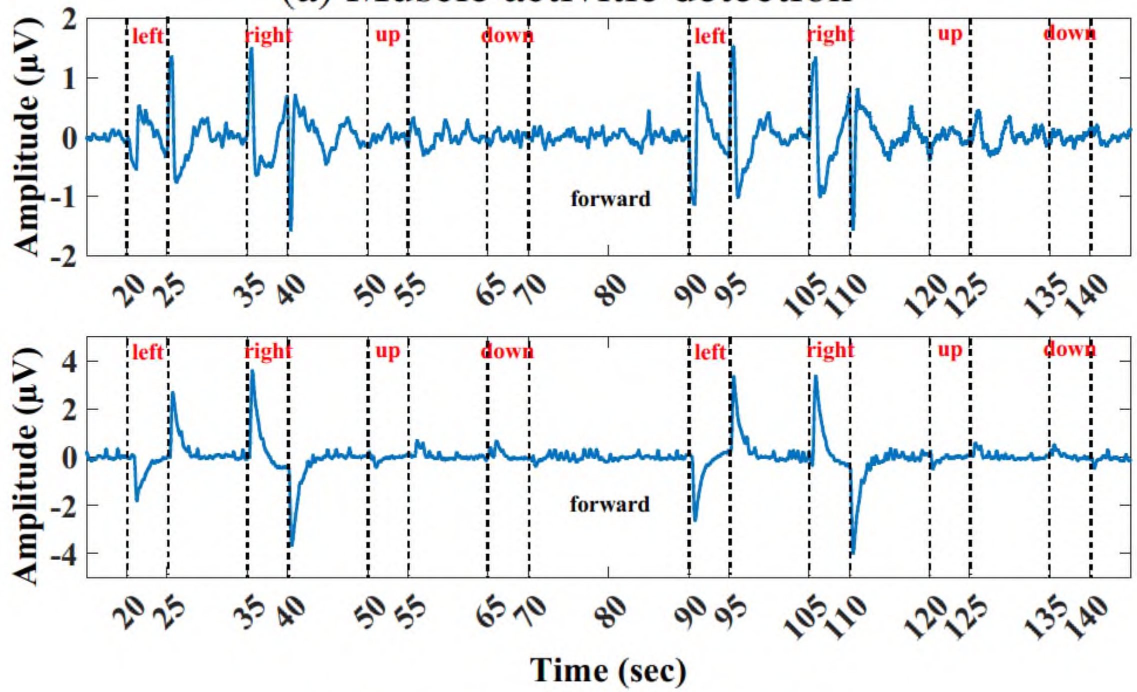
(b) Precision and Recall

Eye and Muscle Activity

- Eye and muscle activity detection



(a) Muscle activitie detection



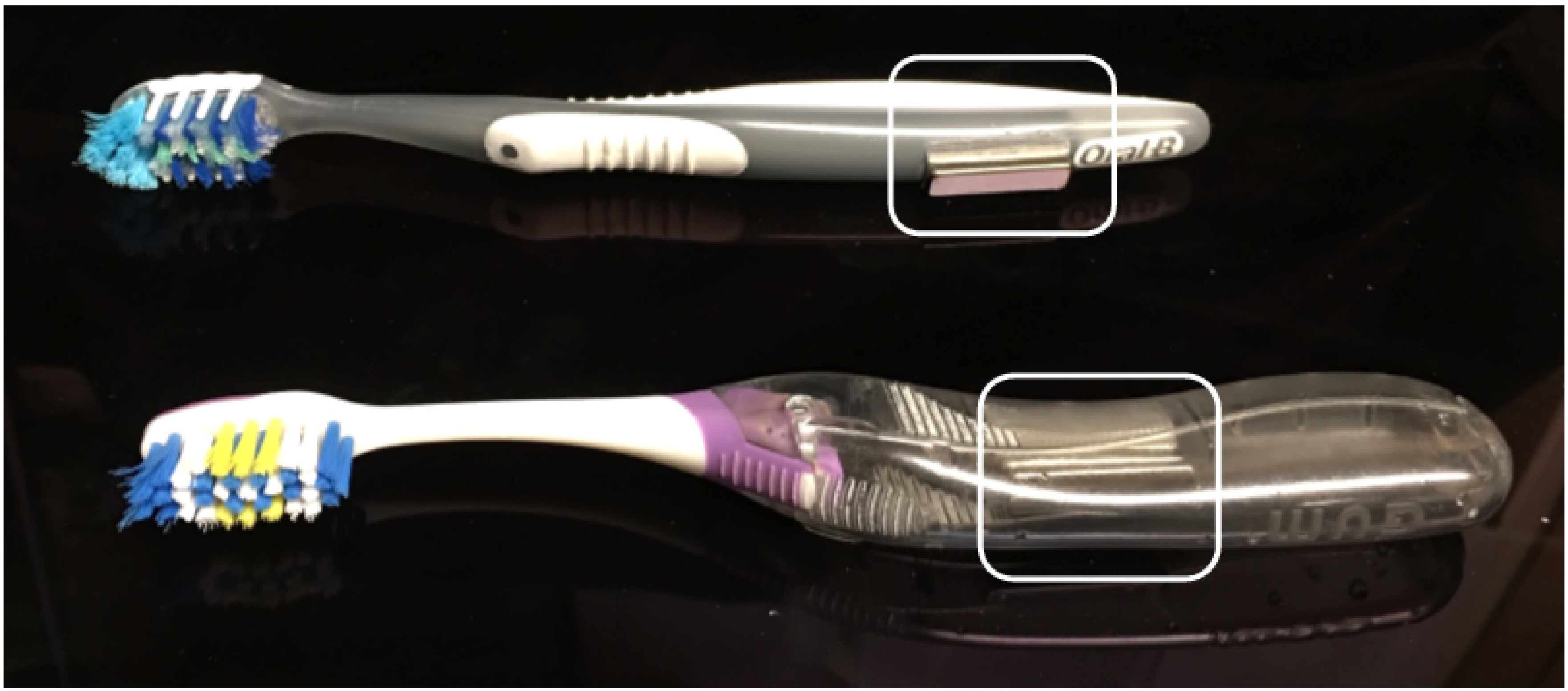
(b) Eye movement detection

User Survey

No.	Survey Statements	SD	Mean
1	*The in-ear device is comfortable to wear during a sleep.*	0.58	4.0
2	*Wearing this device does not include any harmfulness.*	0.76	4.5
3	*I would like to use the in-ear device to evaluate my sleep quality.*	0.68	4.1
4	*Generally, I am satisfied with the use of the in-ear device.*	0.47	4.3
5	*The in-ear device is more comfortable than the on-scalp electrodes of the PSG device.*	0.49	4.4
6	*I did not get disturbed during sleep due to the in-ear device.*	0.75	4.2
7	*I may use the in-ear device every night.*	0.98	4.2
8	*If the in-ear device is wirelessly and it is available for sale, I would like to buy it to assess my sleep quality.*	0.80	4.4

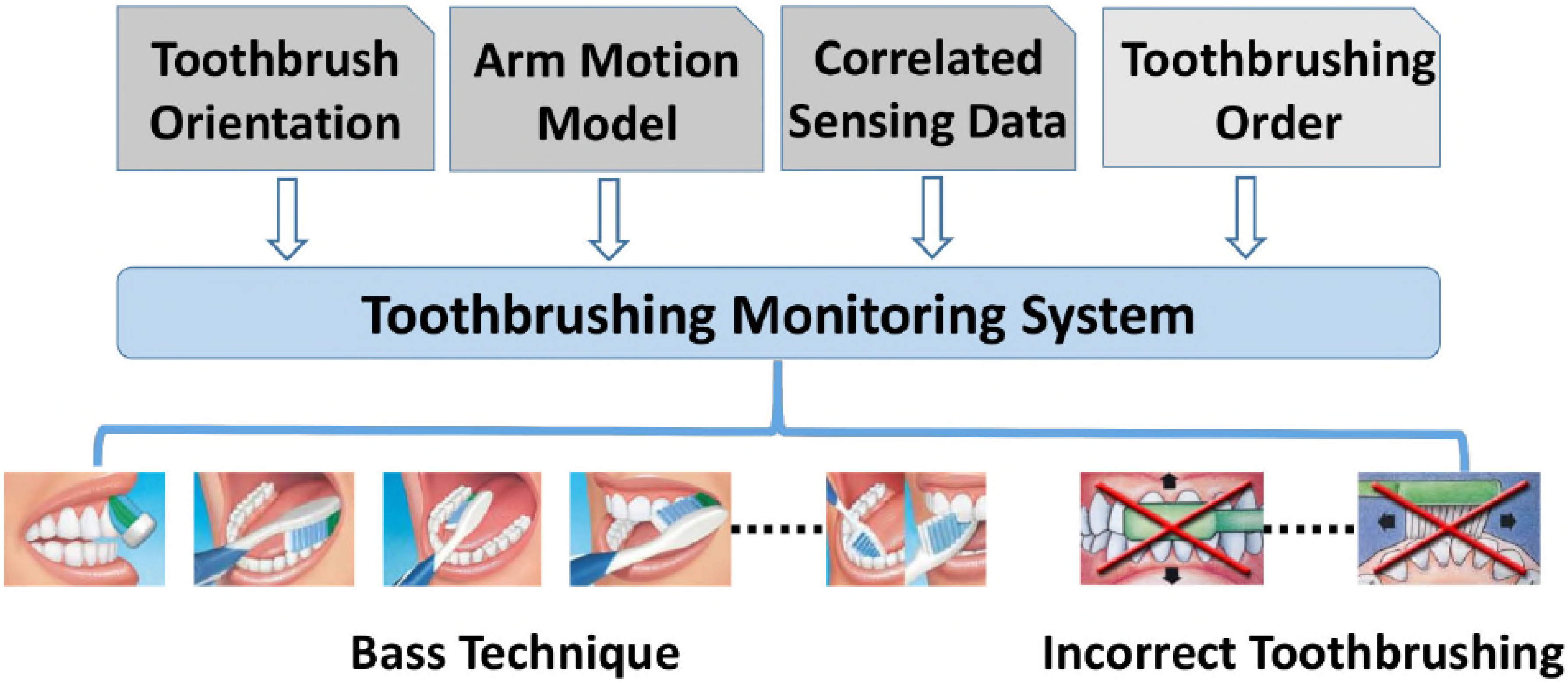
Touthbrush Activity Detection

- Specialized brush



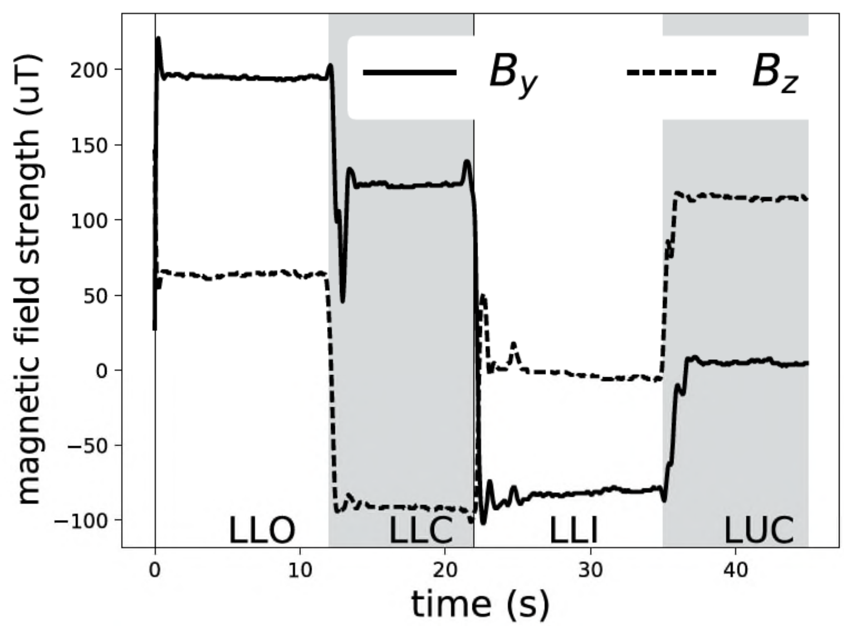
Gesture Recognition

- Modified toothbrush + wrist watch (accelerometer, magnetometer, gyro, acoustic sensor)

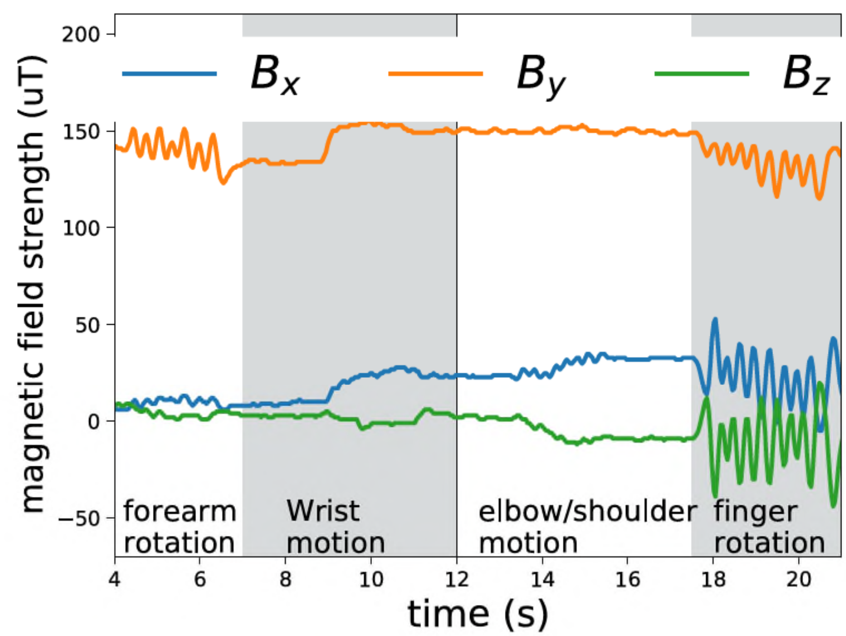


Magnetic detection

- Can recognize basic components of tooth brushing motions

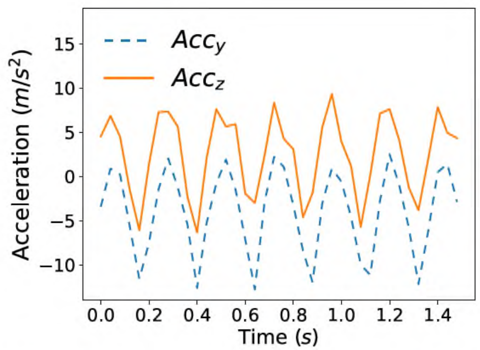


(a) Toothbrush Bristle Orientation

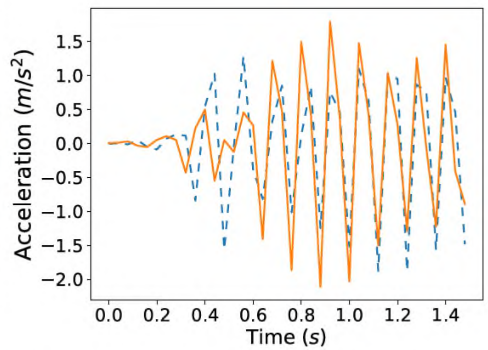


(b) Magnetic Sensing Data under Tooth-brushing Gestures

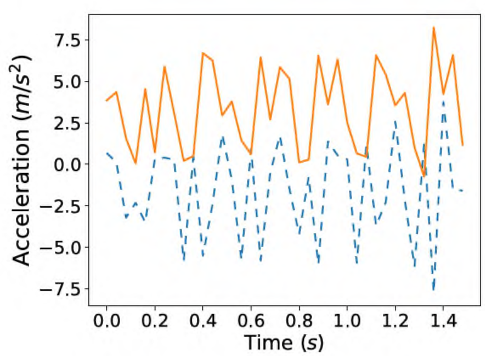
Acceleration



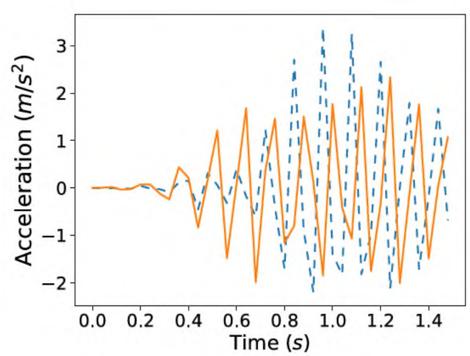
(a) Acceleration Data of Elbow/Shoulder Motion



(b) Band-pass Filtered Acceleration data of Elbow/Shoulder Motion



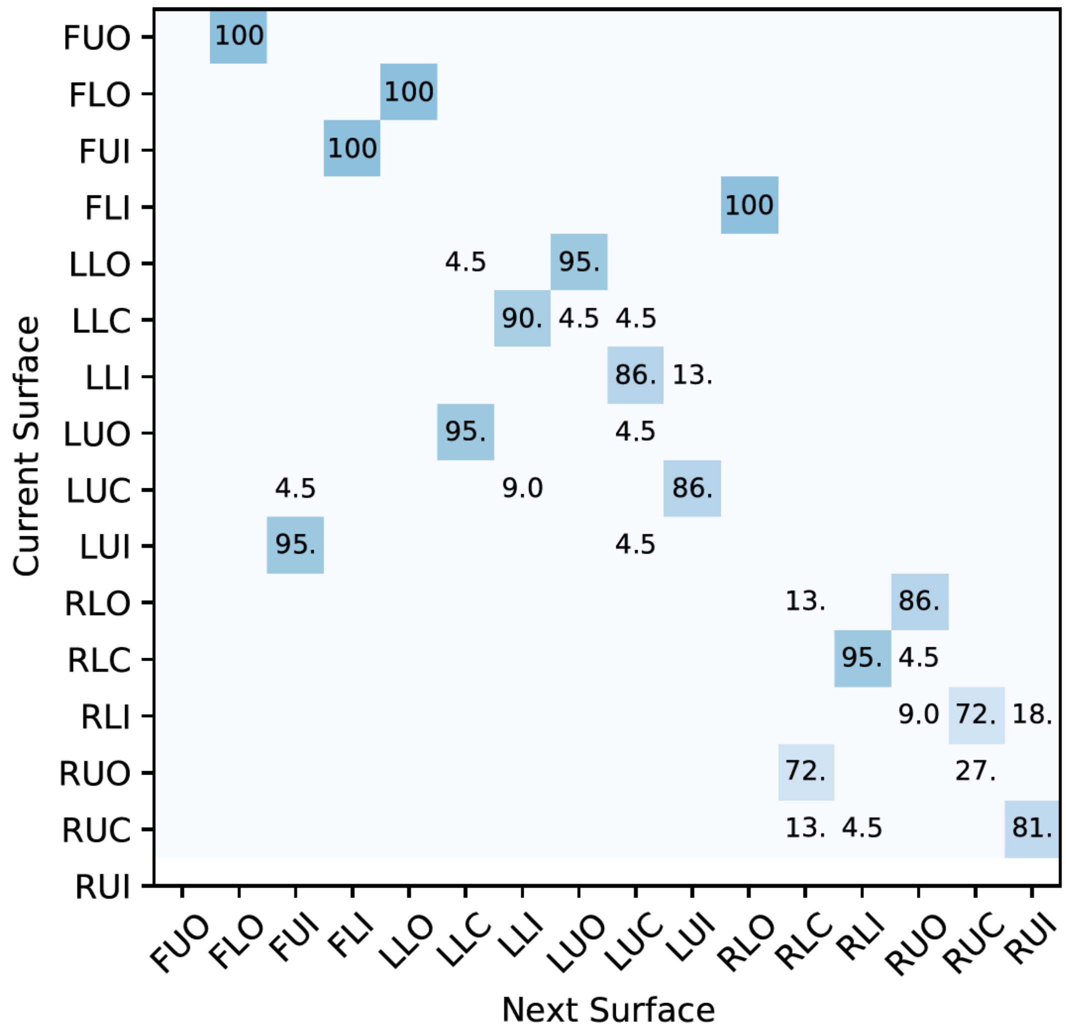
(c) Acceleration data of Wrist Motion



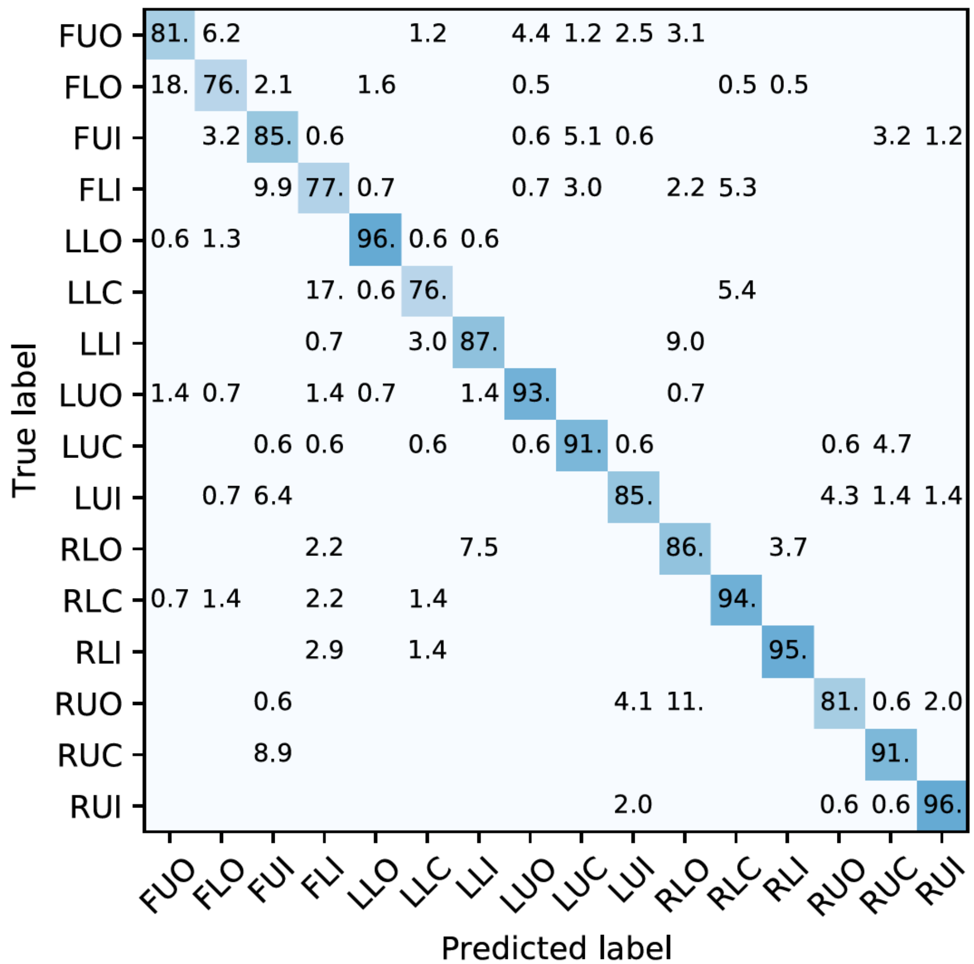
(d) Band-pass Filtered Acceleration data of Wrist Motion

Order and Transition Probabilities

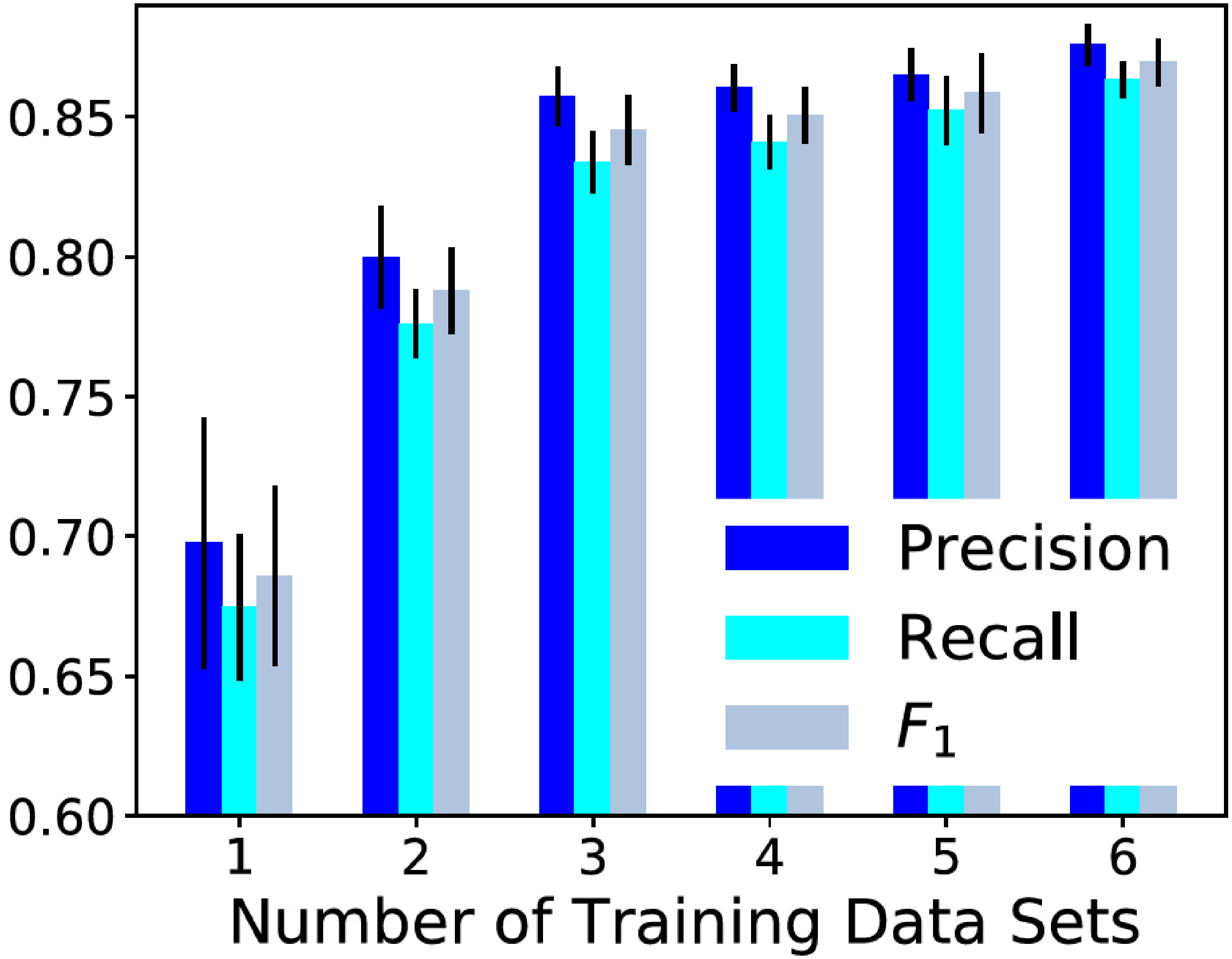
- Detection of individual activities can be improved by understanding linkages among them



Confusion Matrix



Precision and Recall



Hand Hygiene Detection

- Detect proper use of hand hygiene in hospitals

	Accelerometer & Orientation Data set	116 HCW Data set	Geneactiv Data set
Number of Participants	10	116	30
Palm Rub	X		
Fingertip Scrub (R)	X	X	
Fingertip Scrub (L)	X	X	
Interlocking Fingers	X		
Thumb Scrub (R)	X		
Thumb Scrub (L)	X		
Knuckle Twist (R)	X		
Knuckle Twist (L)	X		
Back of Hand (R)	X		
Back of Hand (L)	X		
Wrist Rub (R)	X		
Wrist Rub (L)	X		
Wild		X	X
Walking			
Confounders			X

Valerie Galluzzi, Ted Herman, and Philip Polgreen, "Hand Hygiene Duration and Technique Recognition Using Wrist-worn Sensors," *IEEE/ACM IPSN*, April 2015

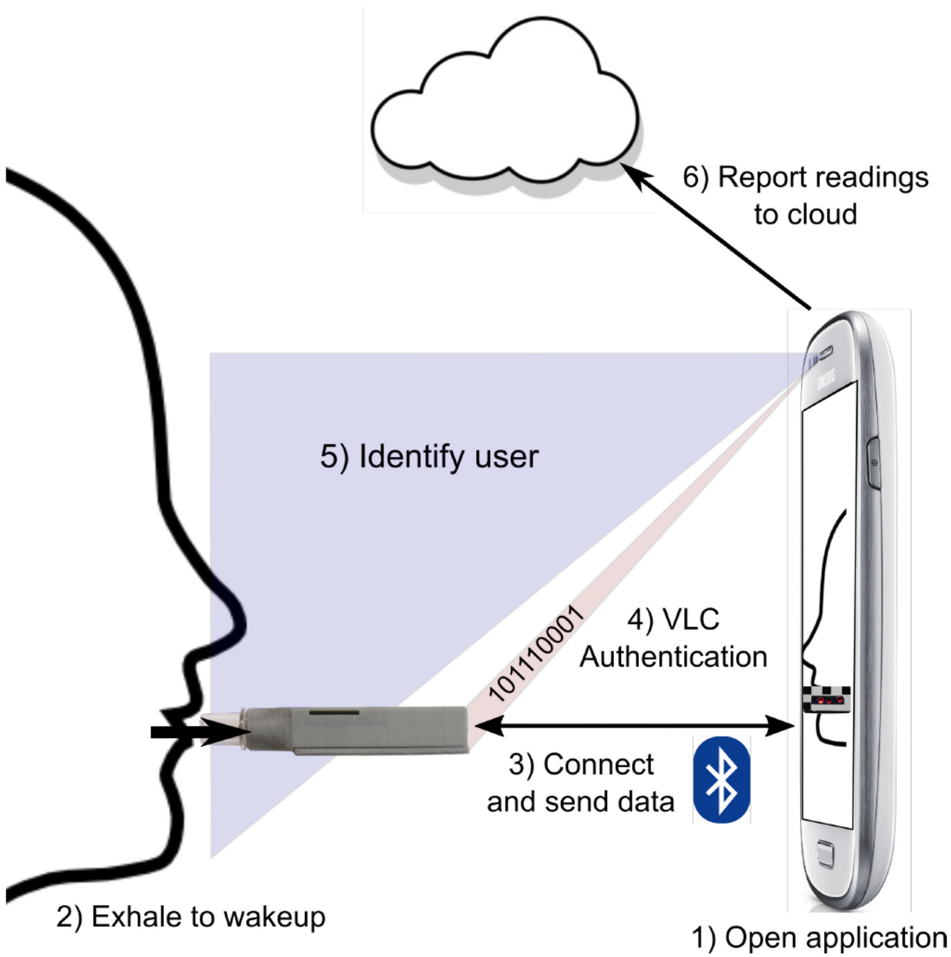
Hand Hygiene Detection

- Detect proper use of hand hygiene in hospitals

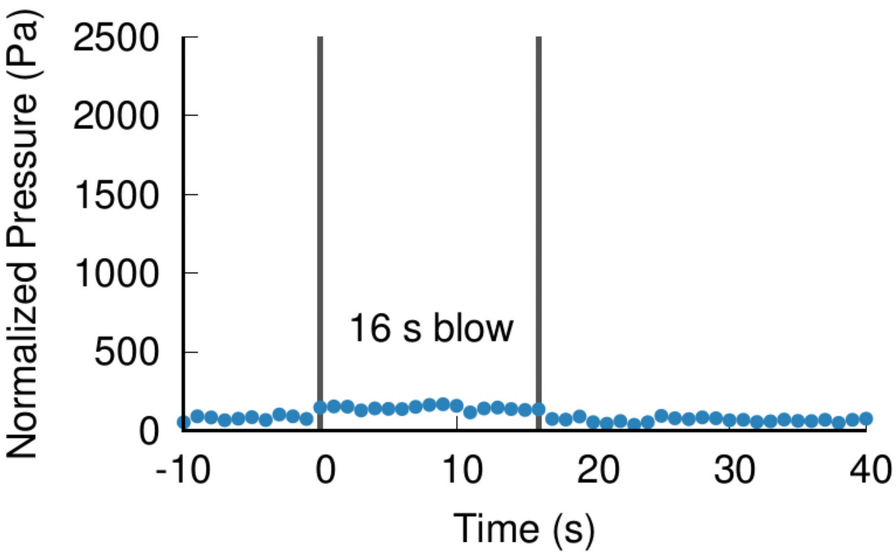
Classified As										
PR	L TS	R TS	L KT	R KT	L FS	R FS	R BH	L BH	IF	True Class
93	0	0	0	0	0	1	0	1	5	PR
0	**87**	8	0	0	0	1	1	4	0	LTS
1	7	**88**	0	0	0	1	1	2	0	RTS
0	2	1	**93**	0	1	0	1	3	0	LKT
0	0	0	0	**98**	0	1	0	1	0	RKT
2	2	1	2	0	**84**	4	3	2	0	LFS
2	1	1	0	3	5	**84**	1	3	0	RFS
1	0	0	0	0	1	0	**91**	7	0	RBH
1	5	1	1	0	1	1	6	**84**	0	LBH
4	0	0	0	0	1	0	0	1	**94**	IF

	116 HCW Data Set	
Classifier	Accuracy	Time (s)
K-Nearest Neighbors	90.2%	0.03
Decision Tree	86.7%	3.44
Neural Network	88.7%	118.03
Naive Bayes	78.1%	0.22
	Geneactiv Data Set	
K-Nearest Neighbors	93.2%	0.01
Decision Tree	92.4%	3.39
Neural Network	93.5%	152.17
Naive Bayes	90.0%	.17
	10 Motion Data Set	
K-Nearest Neighbors	89.5%	0
Decision Tree	83.2%	.55
Neural Network	92.1%	78.3
Naive Bayes	70.0%	.04

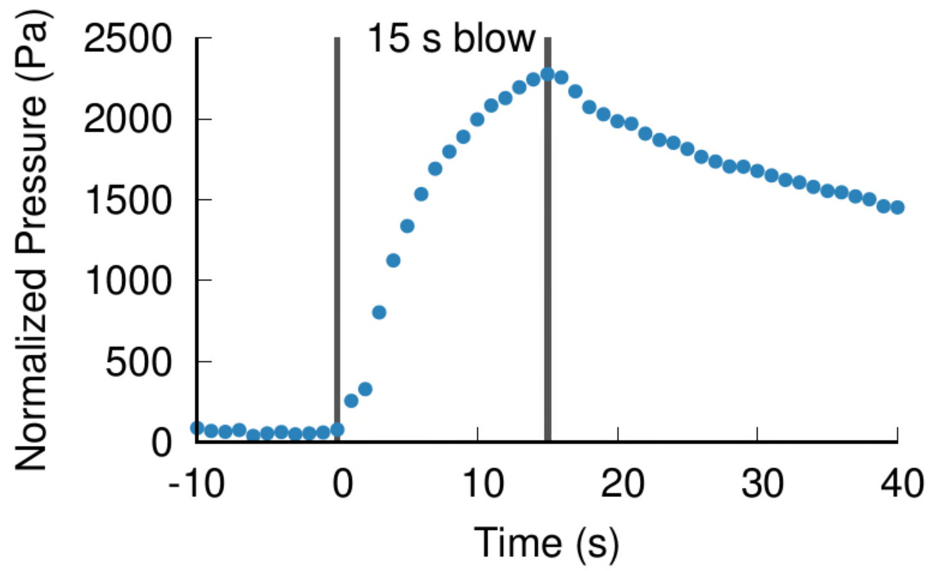
Smoking Detection



Exhalation Verification

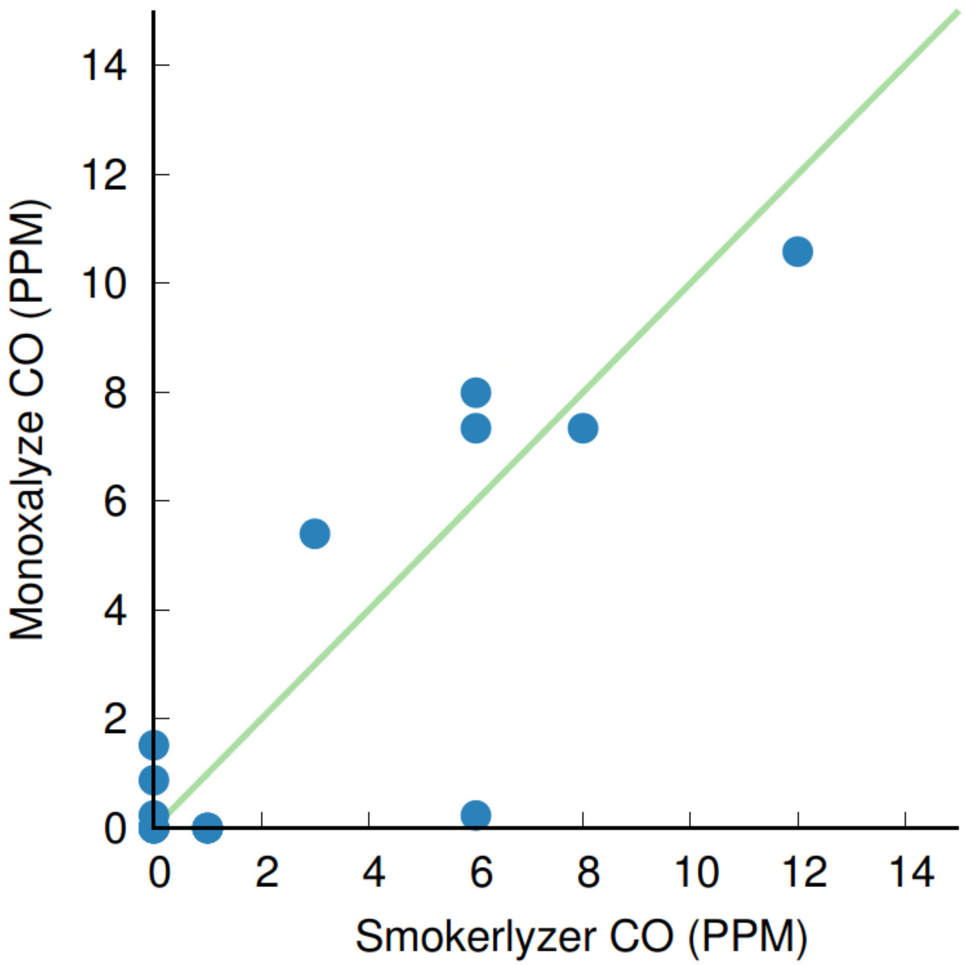


(a) Dry Air



(b) Natural Breath

Accuracy



Monoxalyze CO (PPM)
14
12
10
8
6
4
2
0
0
2
4
6
8
10
12
14
Smokerlyzer CO (PPM)