MATLAB in Wearable Sensing

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Reference studies on wearable sensors

- Inertial sensing
  - Human activity recognition
    - K. Altun, B. Barshan, O. Tunçel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," Pattern Recognition, 43(10), pp. 3605-3620, October 2010.
  - Pedestrian localization
    - K. Altun, B. Barshan, "Pedestrian dead reckoning employing simultaneous activity recognition cues," Measurement Science and Technology, 23(2), 025103, February 2012.
  - Volleyball activity recognition
    - M. E. Özdemir, Wearable systems for performance assessment in volleyball, M.S. Thesis, Izmir Institute of Technology, July 2022
- Touch sensing
  - Hand gesture recognition
    - T. Ballı Altuğlu, K. Altun, "Recognizing touch gestures for human-robot interaction," Proceedings of 17th International Conference on Multimodal Interaction, 9-13 November 2015, Seattle, WA, USA.
  - Sensor error analysis and characterization
    - M. O. Sarp, Error analysis and characterization of piezoresistive array touch sensors, M.S. Thesis, Izmir Institute of Technology, September 2022

Human Activity Recognition Using Body-Worn Inertial Sensors

K. Altun, B. Barshan, O. Tunçel, “Comparative study on classifying human activities with miniature inertial and magnetic sensors,” *Pattern Recognition*, 43(10), pp. 3605-3620, October 2010. **(Citations: 335 WoS, 610 Google Scholar)**

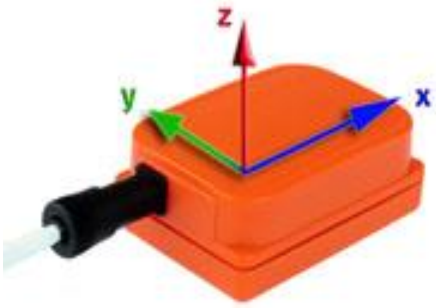
K. Altun, B. Barshan, “Human activity recognition using inertial/magnetic sensor units,” *Human Behavior Understanding*, LNCS vol. 6219, pp. 38-51, August 2010. **(Citations: 175 WoS, 332 Google Scholar)**

Human Activity Recognition

- human activity recognition with body-worn inertial/magnetic sensors
- biomechanics research
- remote monitoring of those in need (e.g., elderly, disabled, children)
- rehabilitation and physical therapy
- sports, dance, animation, virtual reality, ergonomics, ...
- alternative to more widely used camera systems
- sensors can be integrated into body-worn accessories: a necklace, a watch, a cell phone, a hearing aid etc.

Sensor units

- MTx unit by Xsens
  - 3-axial gyroscope
  - 3-axial accelerometer
  - 3-axial magnetometer
- five units are worn:
  - one on the chest
  - two on the legs
  - two on the wrists
- 45 sensors in total

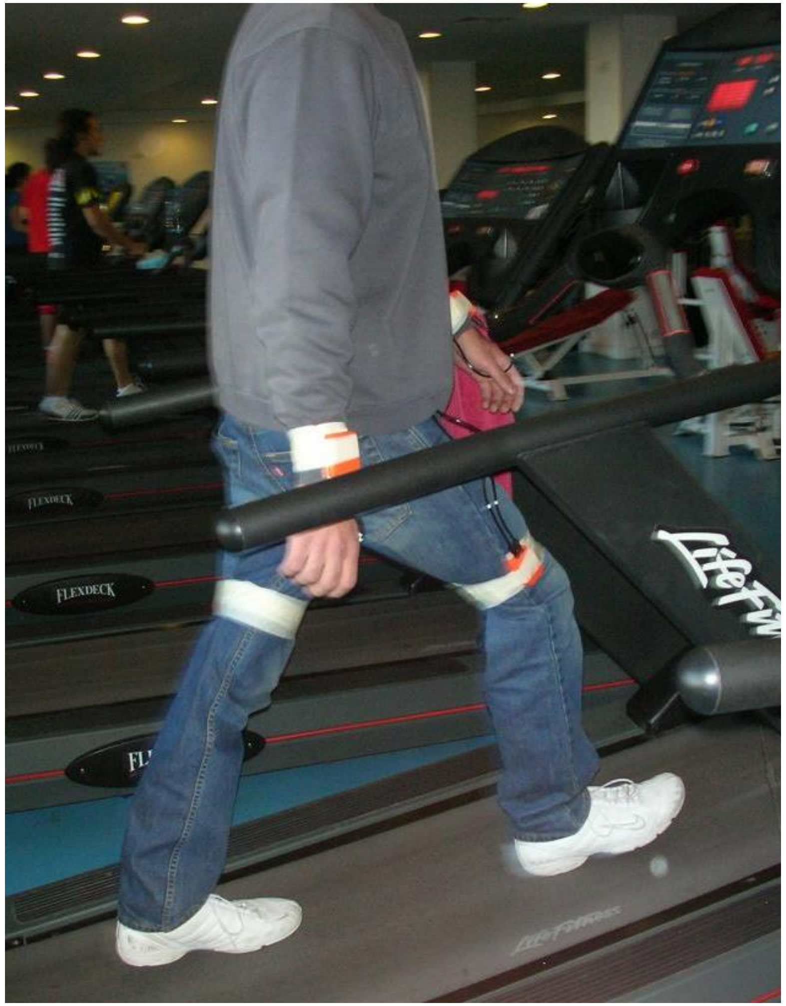


Activities

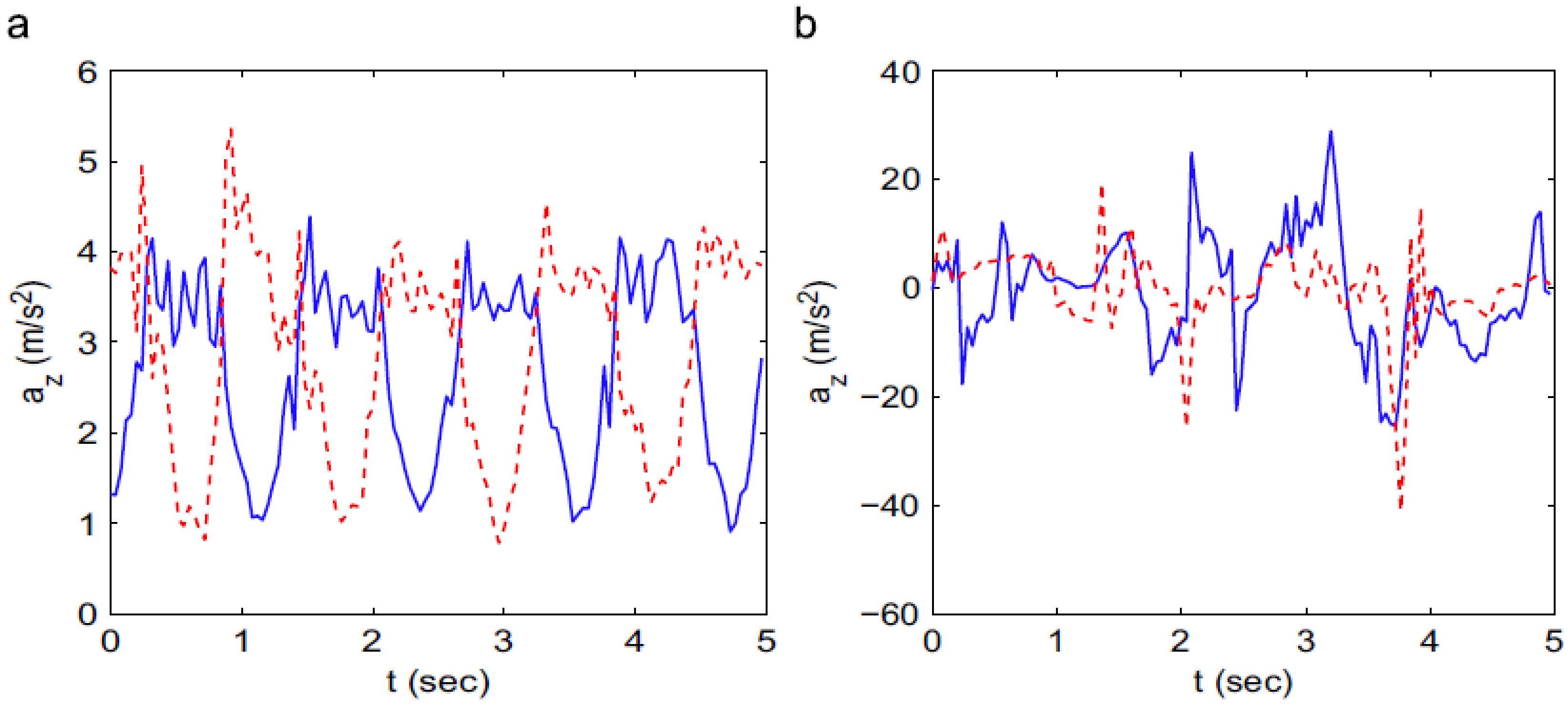
1. sitting
2. standing
3. lying on back
4. lying on right side
5. ascending stairs
6. descending stairs
7. elevator (standing still)
8. elevator (moving around)
9. walking in a parking lot

Activities

10. walking on a horizontal treadmill
11. walking on an inclined treadmill
12. running on a treadmill (8 km/h)
13. exercising on a stepper
14. exercising on a cross trainer
15. cycling on a horizontal exercise bike
16. cycling on a vertical exercise bike
17. rowing
18. jumping
19. playing basketball



Sample signals



walking

basketball

right arm acc

left arm acc

Features

- First four moments (mean, variance, skewness, kurtosis)
- Minimum and maximum values
- Autocorrelation coefficients
- First five peaks and corresponding frequencies of the DFT

- Feature reduction
  - Principal components analysis
  - Sequential forward feature selection

Classification methods

- Bayesian decision making (BDM)
- rule-based algorithm / decision tree (RBA)
- least squares method (LSM)
- k-nearest neighbor (k-NN)
- dynamic time warping (DTW)
- support vector machines (SVM)
- artificial neural networks (ANN)

Results

Method	Correct differentiation rate (%) $\pm$ one standard deviation		
	RRSS	*P*-fold	L1O
BDM	99.1 $\pm$ 0.12	99.2 $\pm$ 0.02	75.8
RBA	81.0 $\pm$ 1.52	84.5 $\pm$ 0.44	53.6
LSM	89.4 $\pm$ 0.75	89.6 $\pm$ 0.10	85.3
k-NN ($k=7$)	98.2 $\pm$ 0.12	98.7 $\pm$ 0.07	86.9
DTW_1	82.6 $\pm$ 1.36	83.2 $\pm$ 0.26	80.4
DTW_2	98.5 $\pm$ 0.18	98.5 $\pm$ 0.08	85.2
SVM	98.6 $\pm$ 0.12	98.8 $\pm$ 0.03	87.6
ANN	86.9 $\pm$ 3.31	96.2 $\pm$ 0.19	74.3

Conclusions

- if training data of a person is available beforehand, a simple classifier with Gaussian distribution assumption (BDM) performs almost perfectly (99% accuracy)
- however, if no training data of that person is available, more complex classifiers (SVM) must be used (85% accuracy)
- sensors on the leg are more discriminative compared to arm and chest sensors
- time domain features are more discriminative than frequency domain features
- possible to obtain ~90% correct recognition rate using one sensor unit only

Simultaneous Human Localization and Activity Recognition

K. Altun, B. Barshan, “Pedestrian dead reckoning employing simultaneous activity recognition cues,” *Measurement Science and Technology*, 23(2), 025103, February 2012. **(Citations: 35 WoS, 52 Google Scholar)**

Motivation

- location is mostly determined using externally-referenced sensors
  - satellites (GPS), cellular networks (GSM), local wireless networks (WiFi, RFID)
- we determine location using body-worn inertial sensors
  - emergency responders
  - underground miners
  - military applications

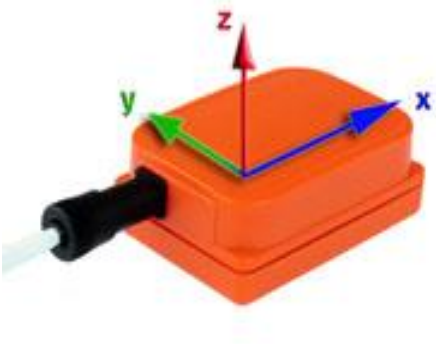
Introduction

- for localization:
  - gyro signals are integrated once (orientation)
  - accelerometer signals are integrated twice (position)
- problem: integration drift – the slightest error in sensor signals cause unbounded error growth in orientation and position
- drifts due to loose mounting on the body, or slips during operation

Introduction

- activity-based map-matching
  - if a map of the environment is available, activity context of the user gives information about position
- we detect switches between activities
  - walking-to-standing (gives position info: in front of elevator, door, etc.)
  - walking-to-stairs (gives position info: at the edge of a staircase)
- perform activity recognition simultaneously with localization

Sensor units

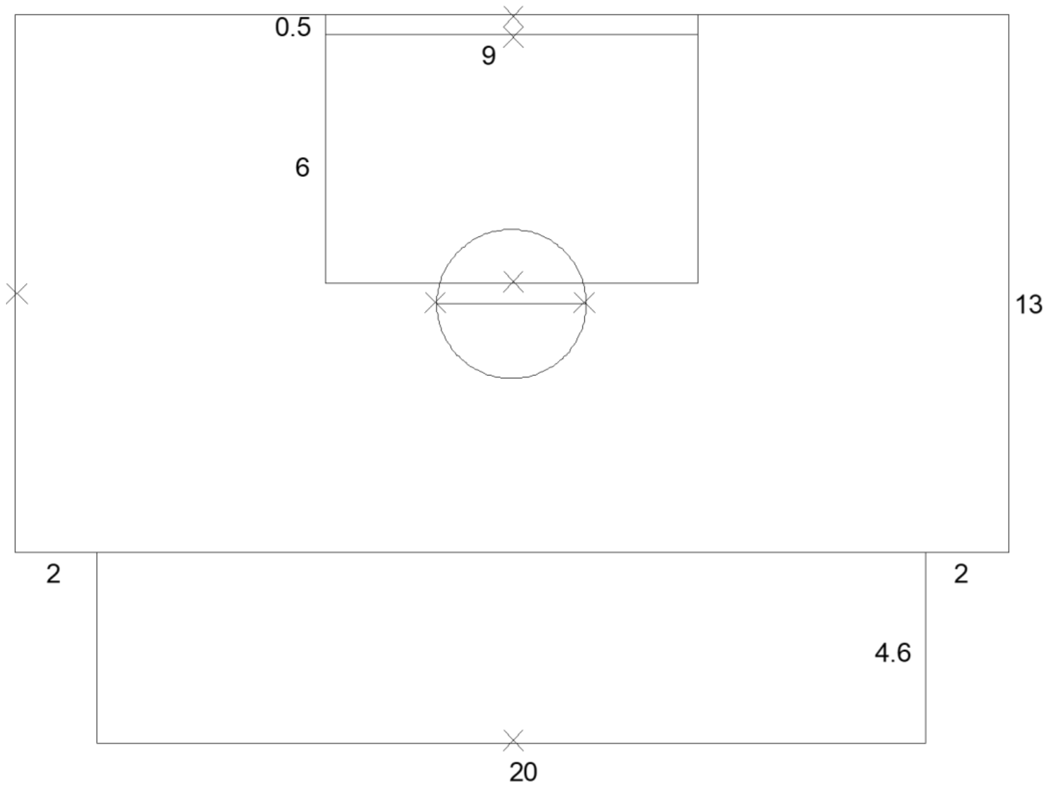


- MTx unit by Xsens
- 3-axial gyroscope
- 3-axial accelerometer
- 3-axial magnetometer
- also provides 3-D orientation through built-in Kalman filter

- five units are worn:
- one on the chest
- two on the legs
- two on the feet

Activity recognition

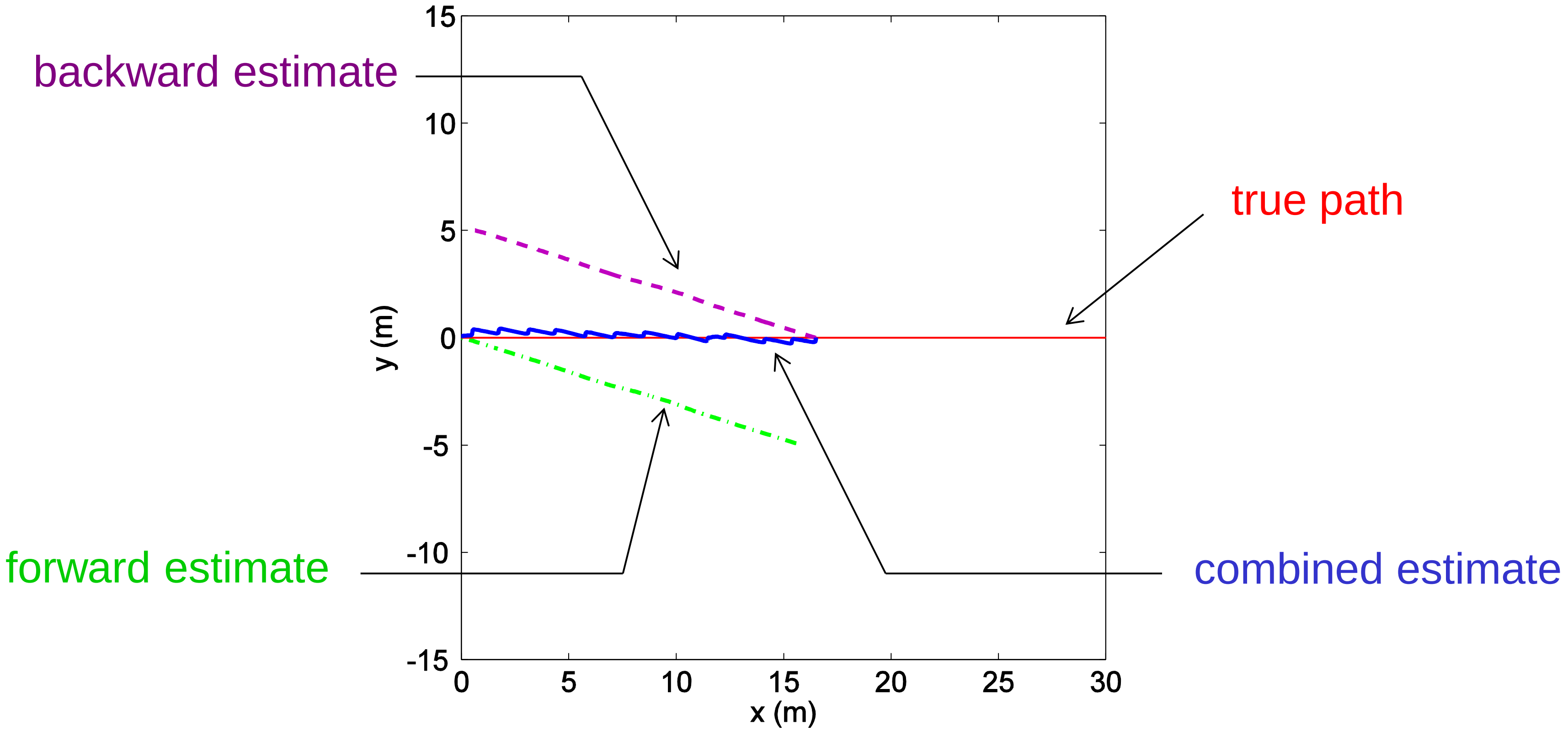
- 2-D case – sports hall
- walking, standing, turning
    - x marks: standing
    - corners: turning



- 3-D case: department building
- walking, standing, turning, stairs

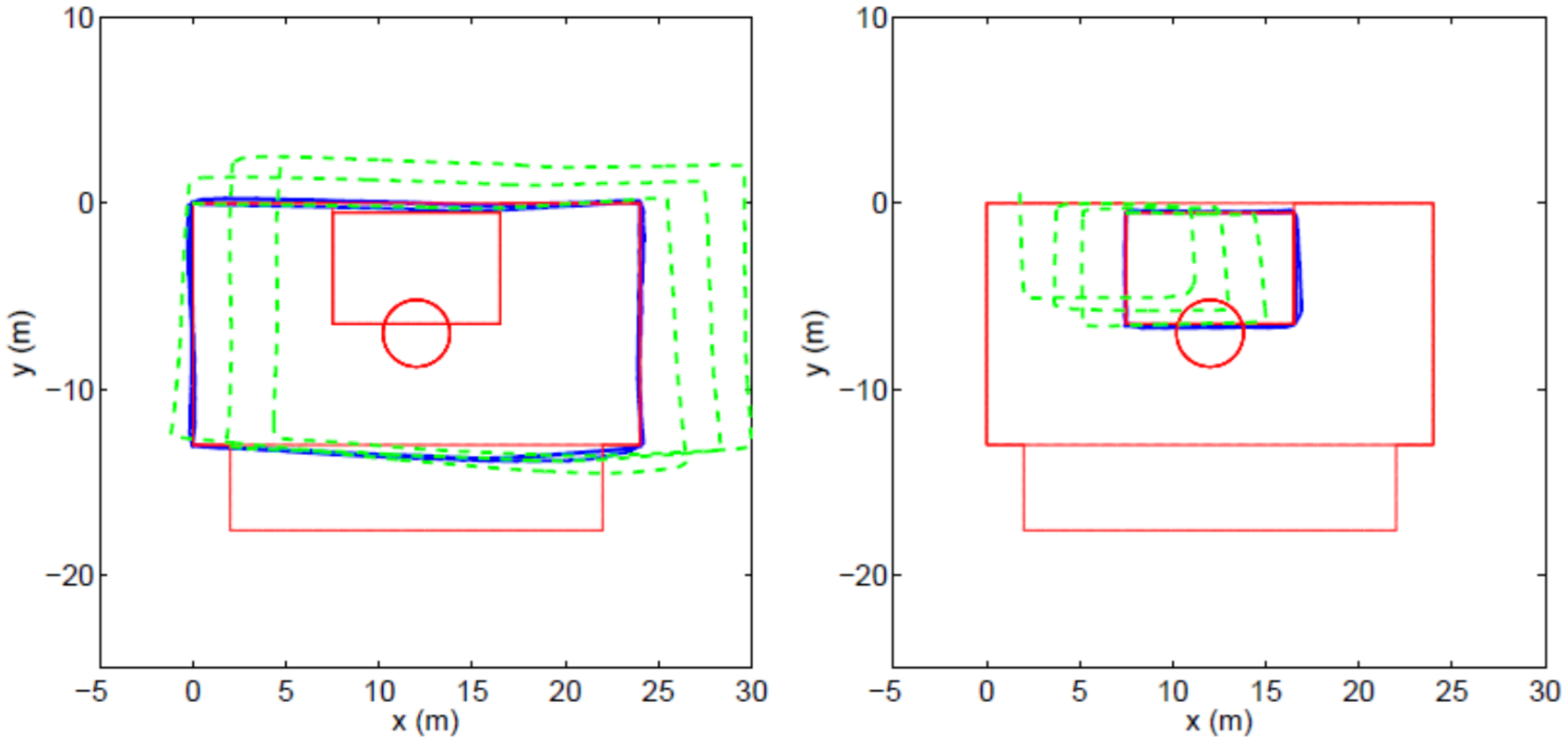
Kalman estimation & smoothing

- motion starts from (0,0), and a walking-to-standing activity switch is detected (at (16,0))



Video showing visualization of the algorithm

Results

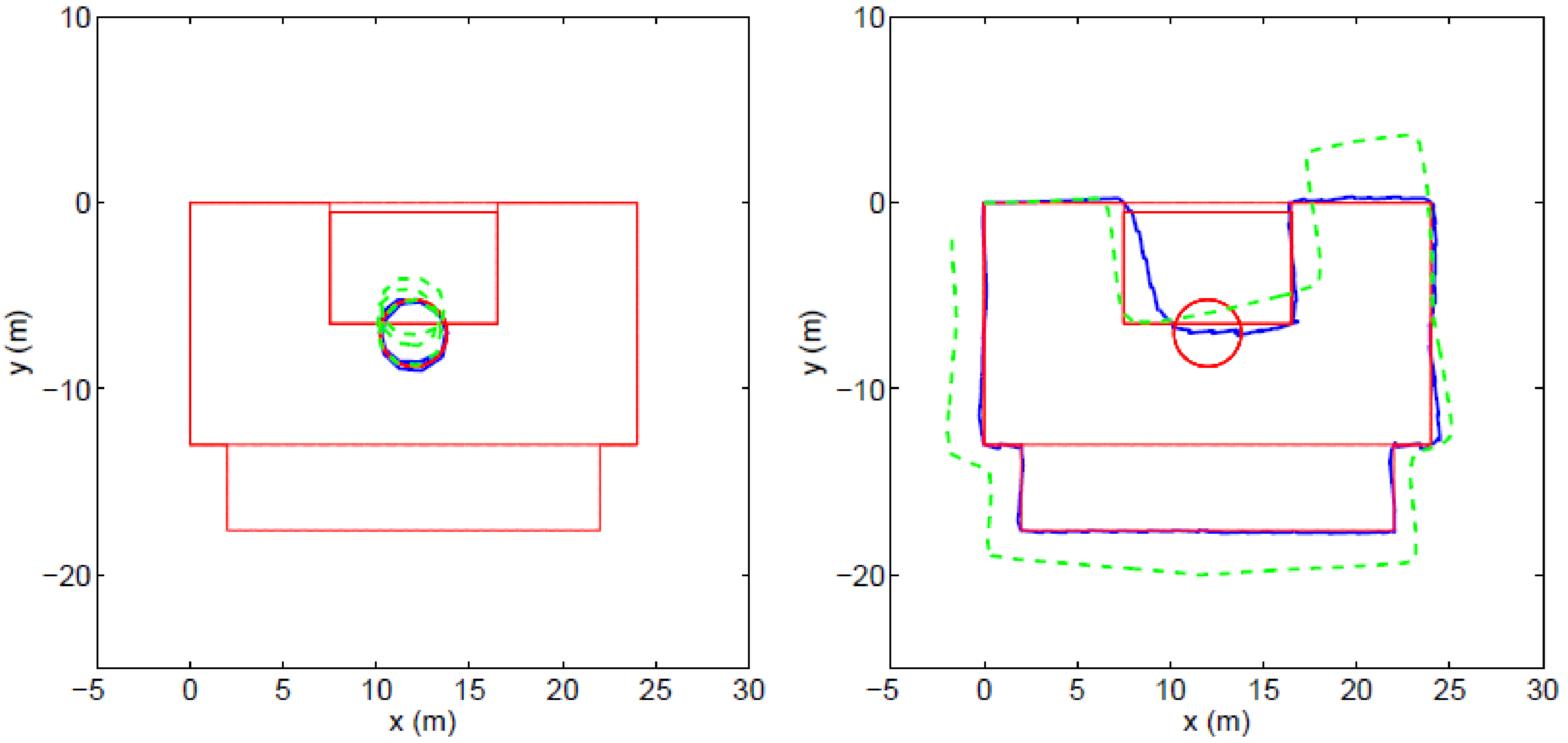


without activity recognition updates

with activity recognition updates

true map

Results

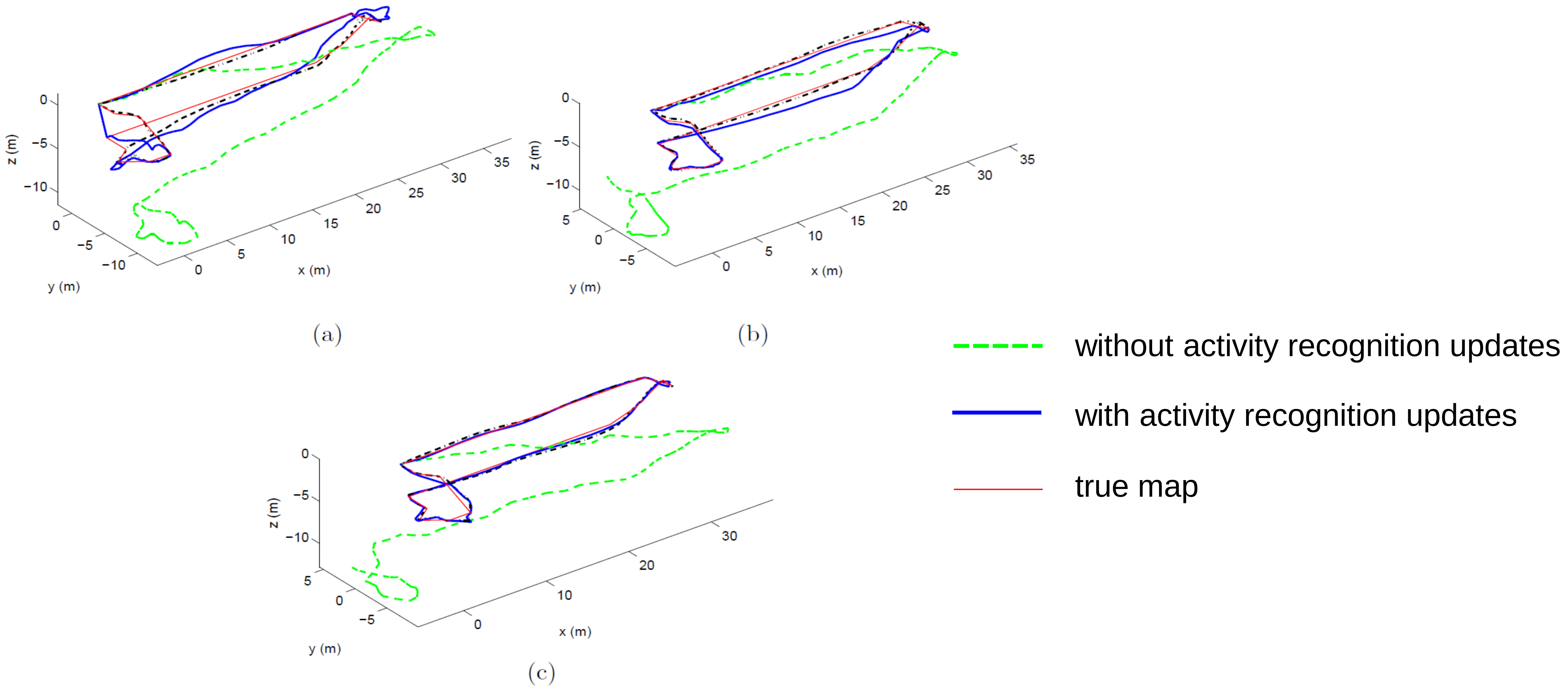


without activity recognition updates

with activity recognition updates

true map

3-D Experiment



Summary

- introduced activity recognition cues to improve localization
- activity recognition cues correspond to locations on a given map, which can be used as position updates
- ~85% reduction in the error can be achieved

Volleyball Activity Recognition

T. Ballı Altuğlu, K. Altun, "Recognizing touch gestures for human-robot interaction," Proceedings of 17th International Conference on Multimodal Interaction, 9-13 November 2015, Seattle, WA, USA.
(Citations: 13 WoS, 25 Google Scholar)

Wearable Systems for Performance Assessment in Volleyball

block

serve

dig

spike

FIGES
applied physics & mathematics

Wearable Systems for Performance Assessment in Volleyball

- In todays' volleyball games, the **classification of attempts realized by players** are executed by human workers/statisticians.

- We aim to show that using wearable sensors, it is possible to **automate** this procedure.

TEAMS AND PLAYERS PERFORMANCES

Won Points	Total Atts	No Name	Scoring Skills	Won Points	Total Atts	No Name
45	**79**	**Total Team**	**Spike**	**43**	**73**	**Total Team**
14	23	8 Wallace		20	29	6 Kurek
11	18	14 Douglas		10	21	13 Kubiak
7	12	17 Evandro		8	15	7 Szalpuk
4	**37**	**Total Team**	**Block**	**10**	**35**	**Total Team**
1	3	5 Lucas Loh		3	4	11 Drzyzga
1	7	16 Lucas		2	7	7 Szalpuk
1	5	1 Bruno		2	6	6 Kurek
2	**70**	**Total Team**	**Serve**	**4**	**77**	**Total Team**
2	10	12 Lipe		2	13	6 Kurek
0	10	14 Douglas		1	7	15 Kochanowski
0	5	13 M. Souza		1	16	1 Nowakowski
18		**Total Team**	**Opp. error**	**21**		**Total Team**
69	**186**	**Total Team**	**Total**	**78**	**185**	**Total Team**
14	32	8 Wallace	**Best scorers**	24	48	6 Kurek
11	29	14 Douglas		12	37	13 Kubiak
7	15	17 Evandro		10	35	7 Szalpuk

■ Starting line-up with position Atts = Attempts (C) = Captain MB = Middle blocker S = Setter
□ Substitute with shirt number Opp. = Opponent L = Libero OP = Opposite spiker WS = Wing spiker

Scoring skills results of Brazil vs Poland 2018 FIVB Volleyball Men's Championship Match

Retrieved on March 30, 2022 from: https://italy-bulgaria2018.fivb.com/en/schedule/9150-brazil-poland/post

Wearable Systems for Performance Assessment in Volleyball

- In this study, we collected data from **5 male and 5 female players** who play at IZTECH volleyball team.

- **5 Xsens MTw Awinda sensors** are used
    - 3D angular velocity, 3D acceleration, 3D earth magnetic field

- Each player performed **4 main actions**:

- **12 spikes** (4 times from different zones which are respectively 4^{th}, 3^{rd} and 2^{nd})

- **12 blocks** (4 times from different zones which are respectively 3^{rd} , 4^{th} and 2^{nd})

- **12 digs** (4 times for 3 different modes which are respectively from middle, left and right)

- **10 float serves**

One of our volunteers with sensors placed on the body

Sample confusion matrix

		CLASSIFIED									
		MD	LD	RD	MB	LB	RB	SRV	LSP	MSP	RSP
TRUE	MD	39	0	1	0	0	0	0	0	0	0
	LD	0	36	4	0	0	0	0	0	0	0
	RD	0	5	35	0	0	0	0	0	0	0
	MB	0	0	0	40	0	0	0	0	0	0
	LB	0	0	0	0	40	0	0	0	0	0
	RB	0	0	0	2	0	36	0	0	0	2
	SRV	0	0	0	0	0	0	100	0	0	0
	LSP	0	0	0	0	0	2	0	27	8	3
	MSP	0	0	0	0	0	0	0	2	35	3
	RSP	0	0	0	0	1	0	0	4	5	30

Wearable Systems for Performance Assessment in Volleyball

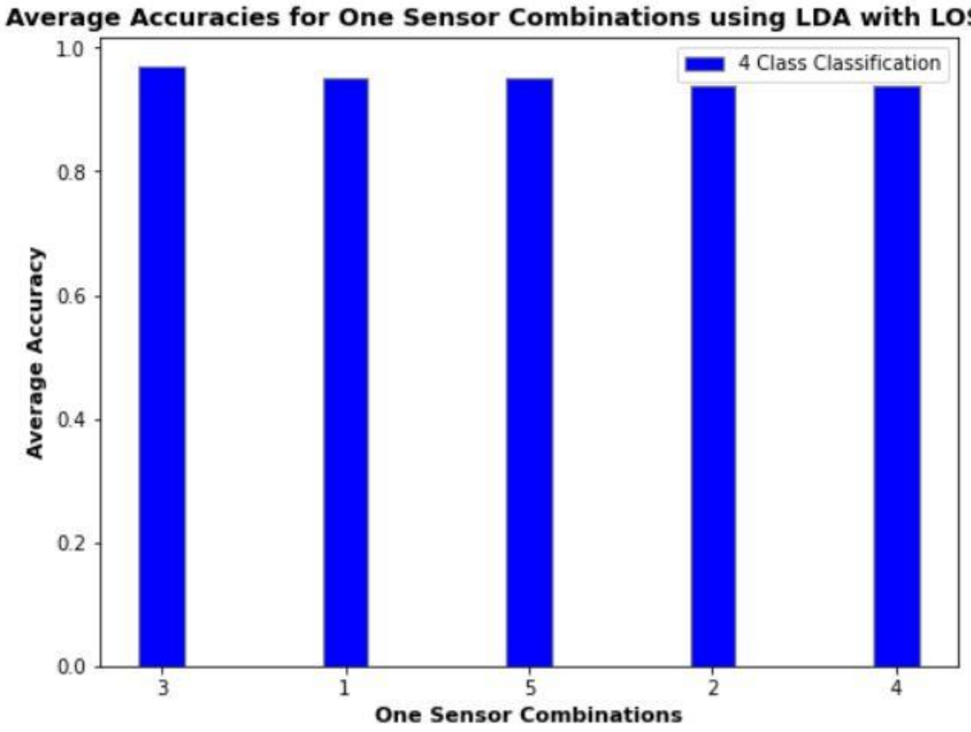
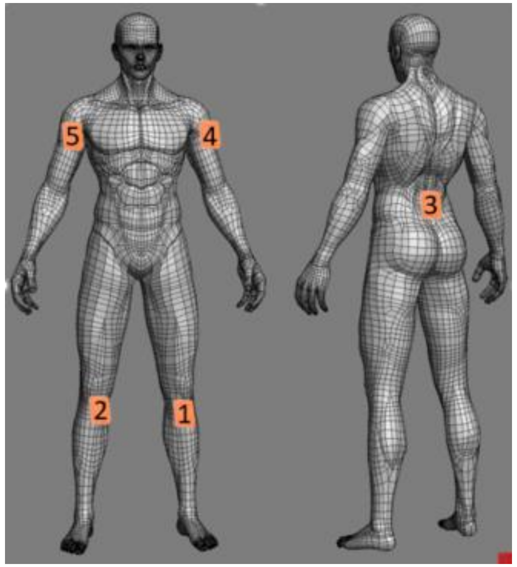


Figure 24: One-Sensor Combinations using LDA with LOSO CV for 4-Class Classification



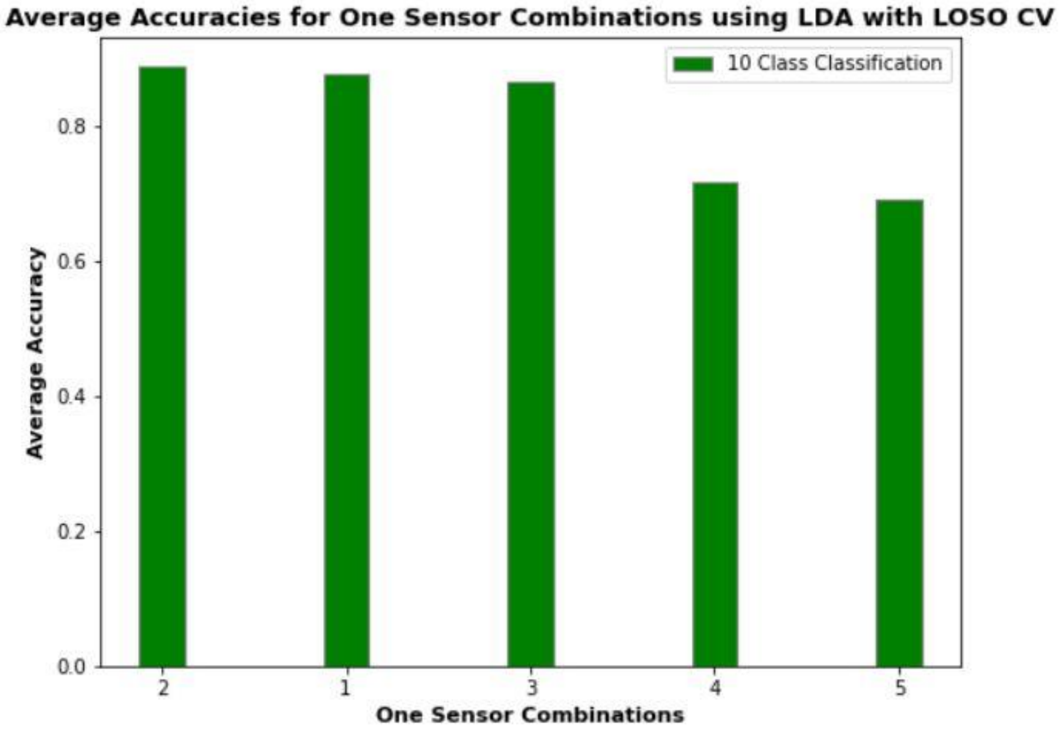


Figure 25: One-Sensor Combinations using LDA with LOSO CV for 10-Class Classification

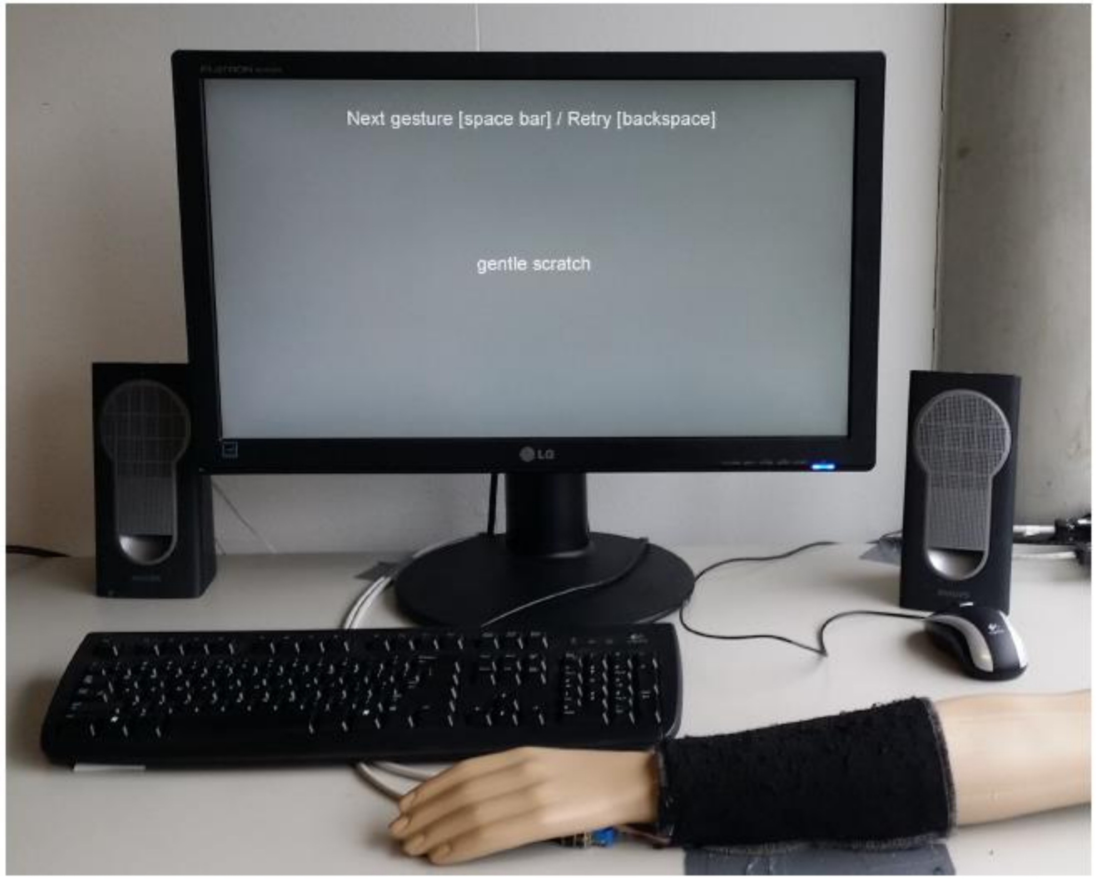
Touch Gesture Recognition

T. Ballı Altuğlu, K. Altun, "Recognizing touch gestures for human-robot interaction," Proceedings of 17th International Conference on Multimodal Interaction, 9-13 November 2015, Seattle, WA, USA.

(Citations: 13 WoS, 25 Google Scholar)

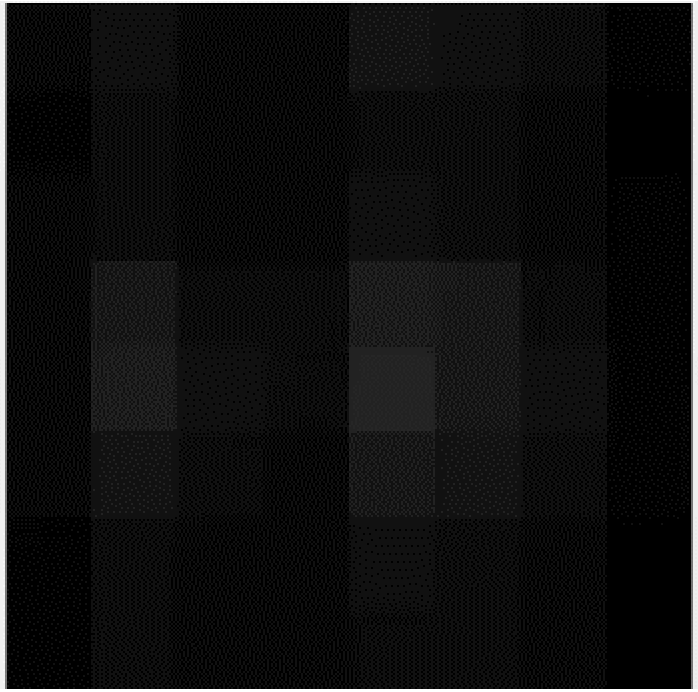
Dataset: CoST – Corpus of Social Touch
(Jung et al., 2014)

- 14 gestures: grab, hit, massage, pat, pinch, poke, press, rub, scratch, slap, squeeze, stroke, tap, tickle
- Gestures performed by 31 subjects in 3 variations (normal, gentle, rough)
- Touch sensor wrapped around a mannequin arm
  - measures the pressure applied in an 8x8 grid
- Pressure values sampled at 135 Hz, quantized in 10 bits (0—1023 range)

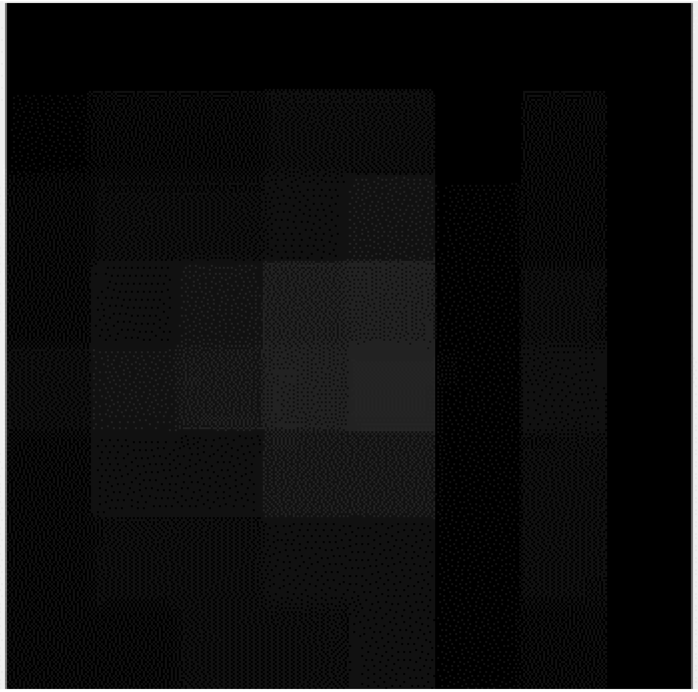


Examples

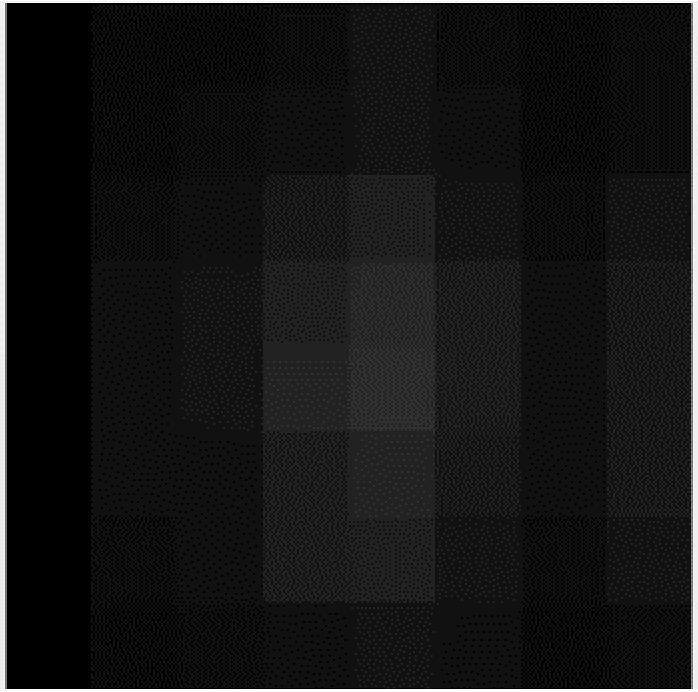
pat



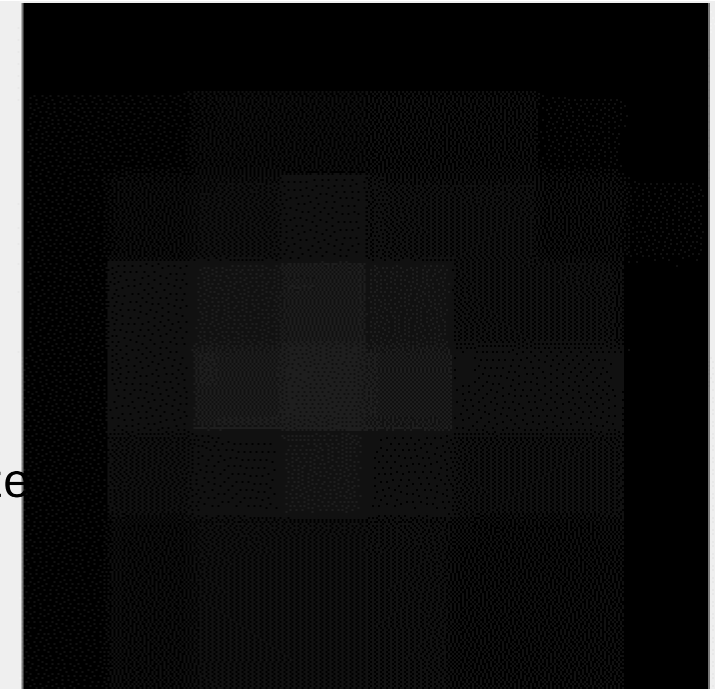
rub



scratch



squeeze



Features

- Calculate features from video
  - mean pressure
  - centroid
  - polar moment of the image
  - max. pressure and its location

- From every signal, calculate
  - Mean, variance, max, min, median, energy, autoregressive model coefficients

- Threshold each frame with the mean pressure
  - Area
  - Convex hull
  - Solidity
  - Major/minor axes length
  - Eccentricity
  - Orientation
  - Equivalent diameter

Results

Table 6: Confusion matrix for Case (v).

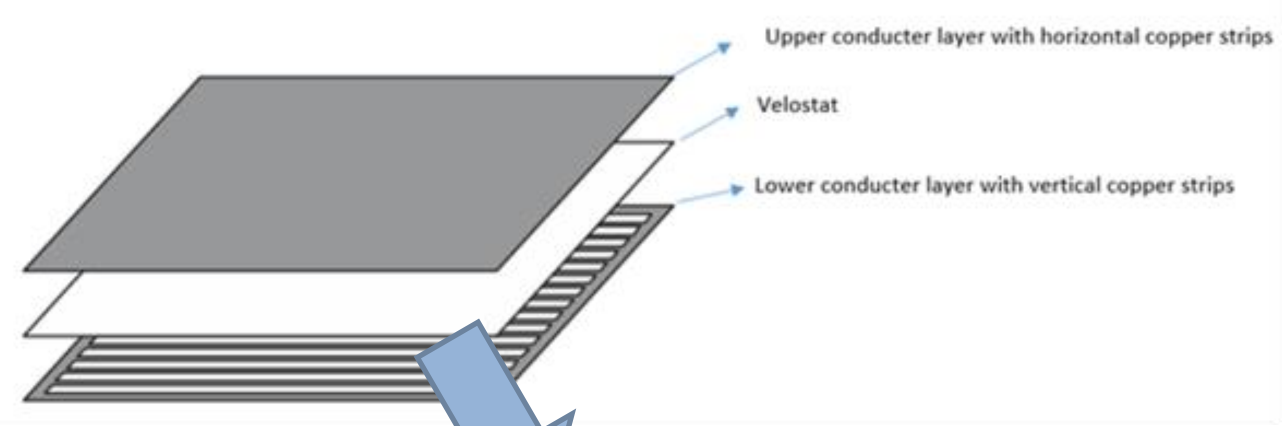
	grab	hit	massage	pat	pinch	poke	press	rub	scratch	slap	squeeze	stroke	tap	tickle
grab	**83**	0	2	0	1	0	1	1	2	0	25	4	0	1
hit	0	**75**	0	5	1	9	0	0	0	20	0	0	9	1
massage	8	0	**79**	0	2	1	1	6	2	0	4	7	0	10
pat	0	21	0	**51**	0	5	1	0	1	14	0	3	23	1
pinch	1	2	3	0	**76**	10	19	2	0	0	5	2	0	0
poke	0	4	0	1	8	**90**	1	0	0	0	0	0	16	0
press	10	0	0	0	9	1	**80**	4	2	0	12	1	0	1
rub	4	0	11	0	1	0	15	**42**	8	0	0	30	0	9
scratch	1	0	5	2	1	3	1	16	**51**	1	1	11	1	26
slap	0	35	0	3	0	6	0	0	0	**58**	0	0	17	1
squeeze	55	0	5	0	5	0	2	0	0	0	**52**	0	0	0
stroke	0	1	1	2	10	3	1	10	8	1	0	**77**	2	4
tap	0	24	0	23	0	12	3	0	0	16	0	0	**41**	1
tickle	0	0	2	10	2	0	0	4	24	0	0	3	2	**73**

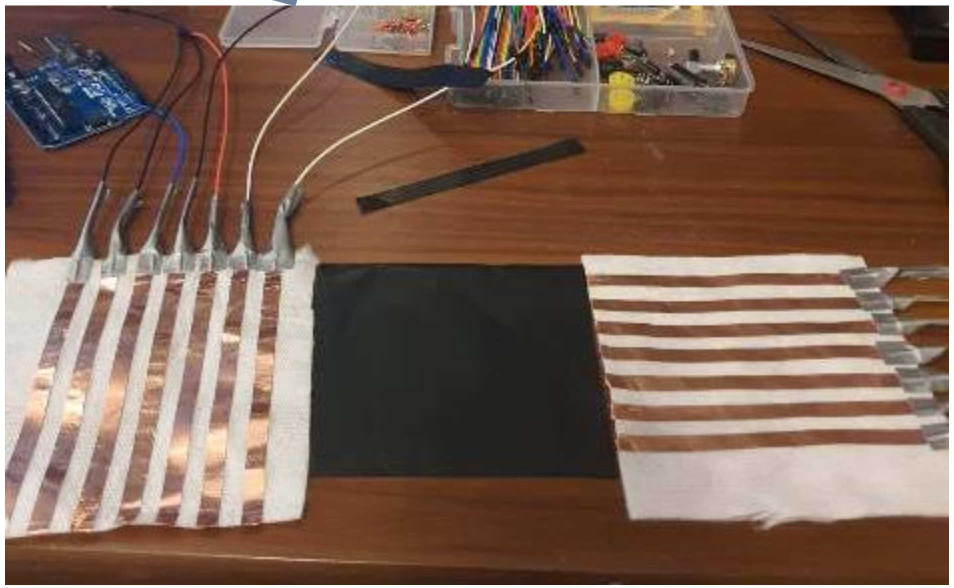
Error Characterization of Touch Sensors

M. O. Sarp, Error analysis and characterization of piezoresistive array touch sensors, M.S. Thesis, Izmir Institute of Technology, September 2022

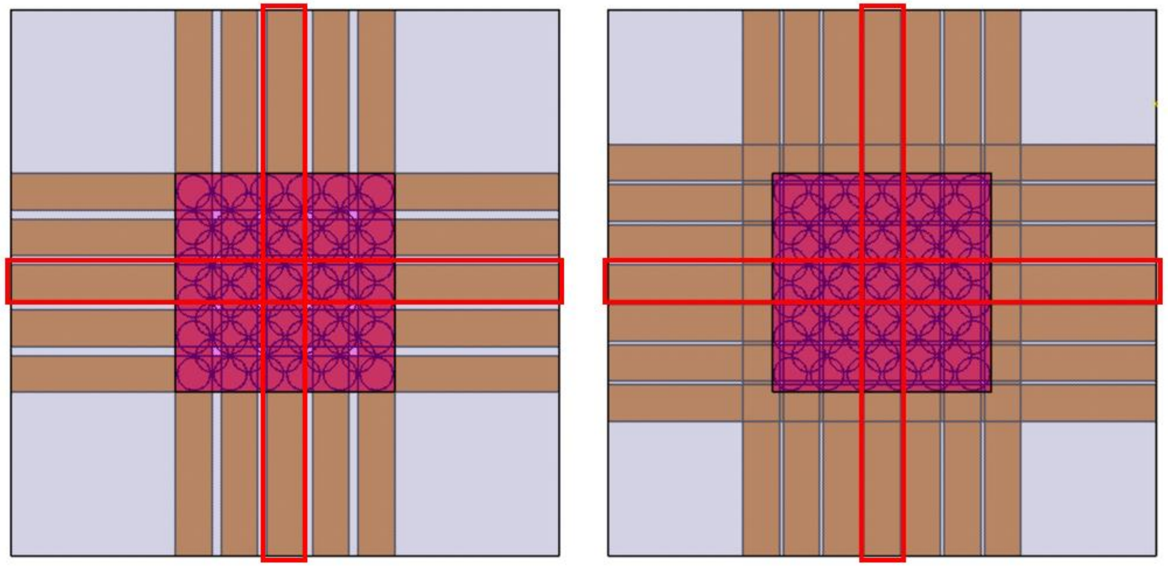
Error characterization of piezoresistive array touch sensors

- M.S. Thesis by Mehmet Ogün Sarp, September 2022
- Determine the error characteristics of a **low-cost** sensor
- Determine resolution of
  - Touch location
  - Touch intensity
- For various sensor parameters



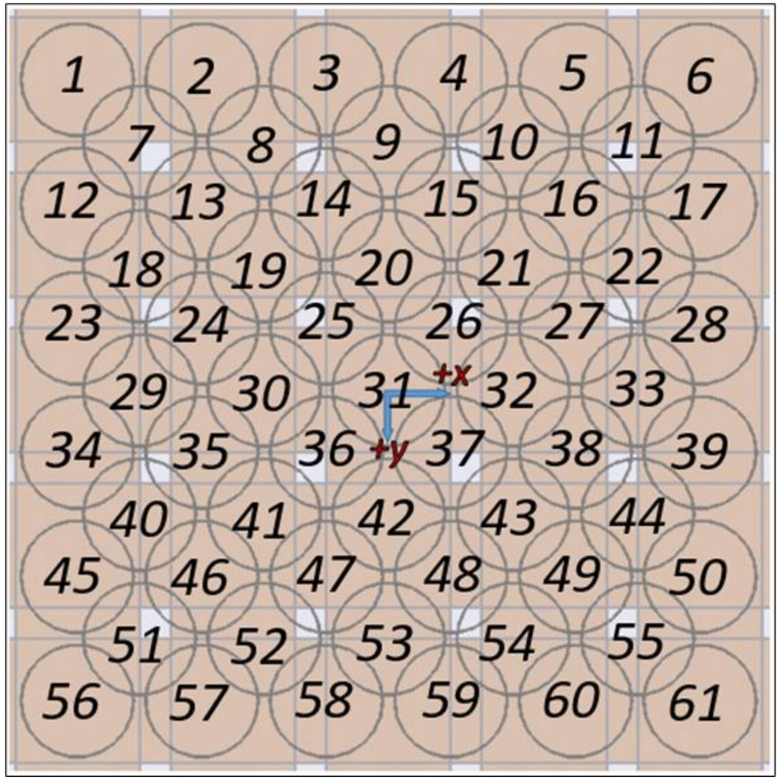


Error characterization of touch sensors

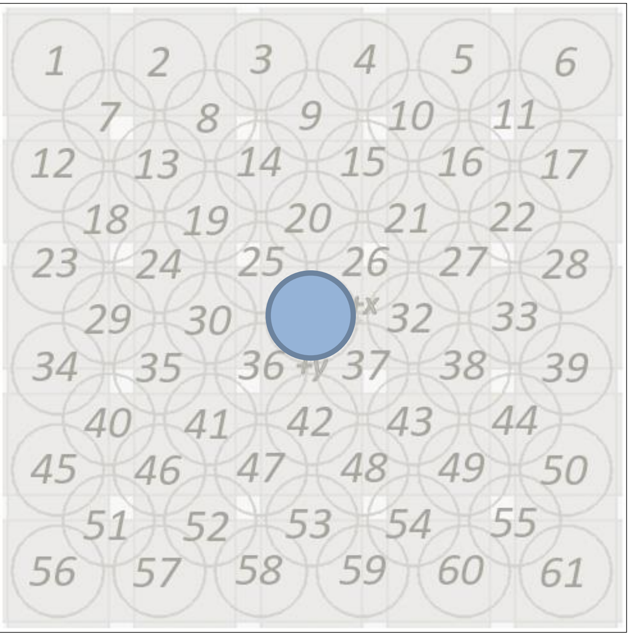


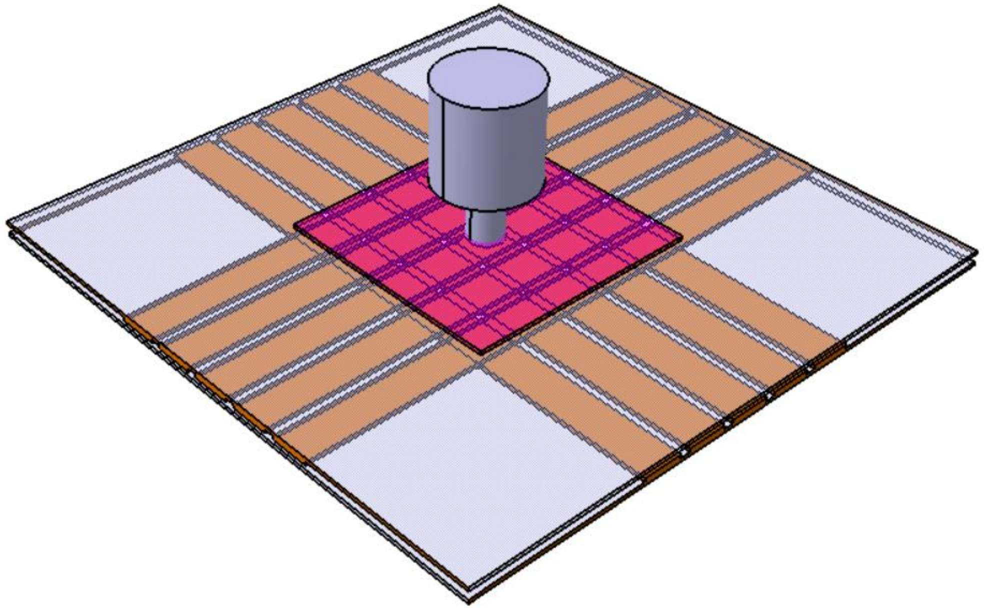
25 Sensor Points with 2.5mm Gaps   49 Sensor Points with 1mm Gaps

2 different sensor arrays; 5x5 and 7x7



Error characterization of touch sensors





LOADED

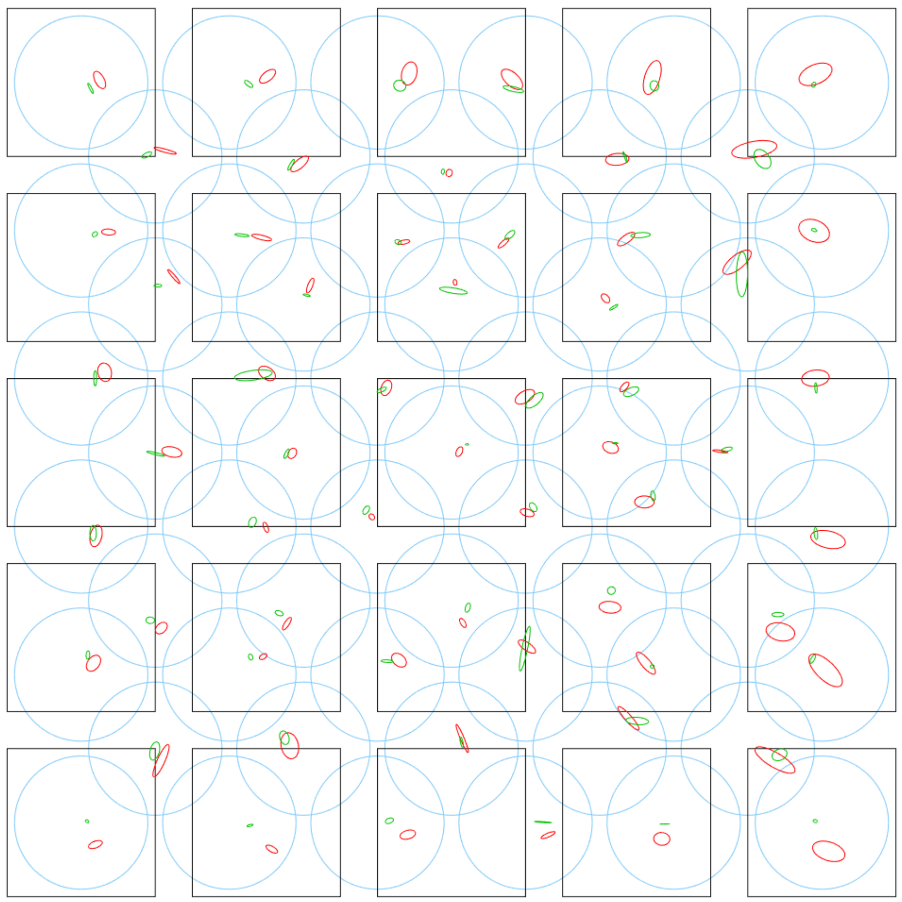
2	5	15	1	0
1	5	31	6	2
18	28	501	41	10
3	2	8	0	1
0	1	8	4	0

pressure map

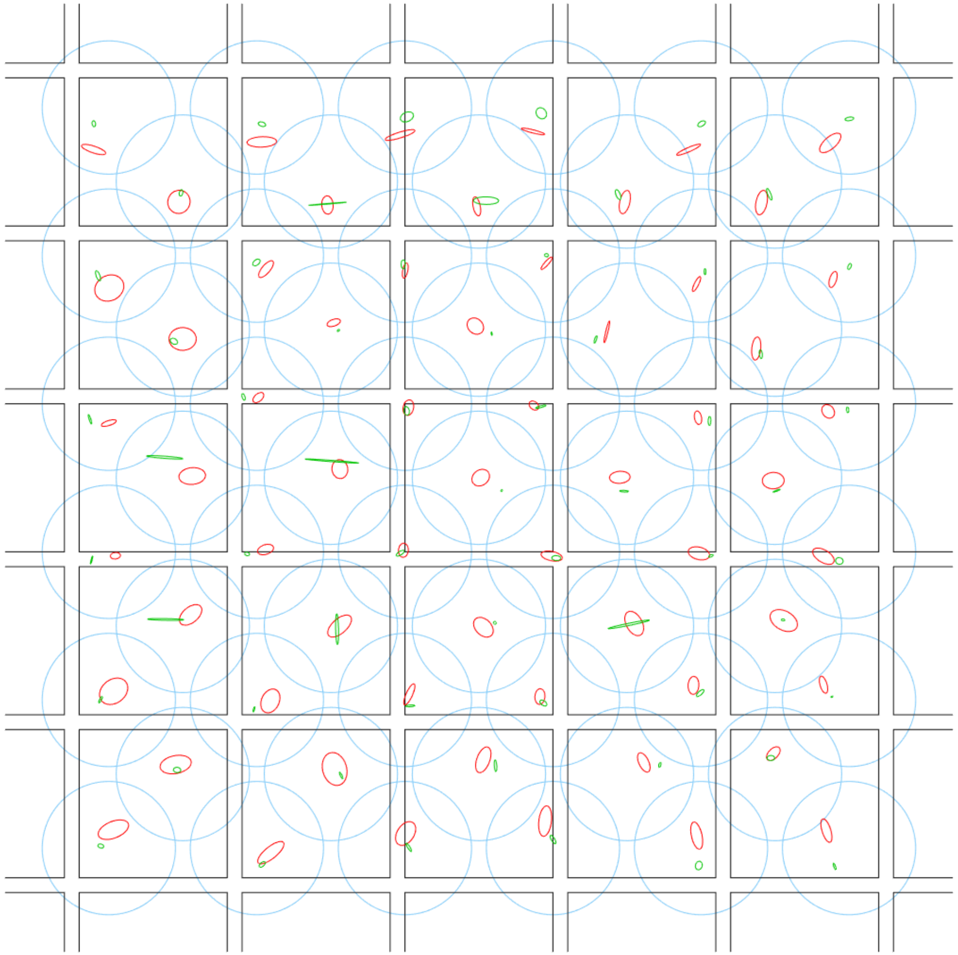
Error ellipses for touch points

raw data

2x2 subarray

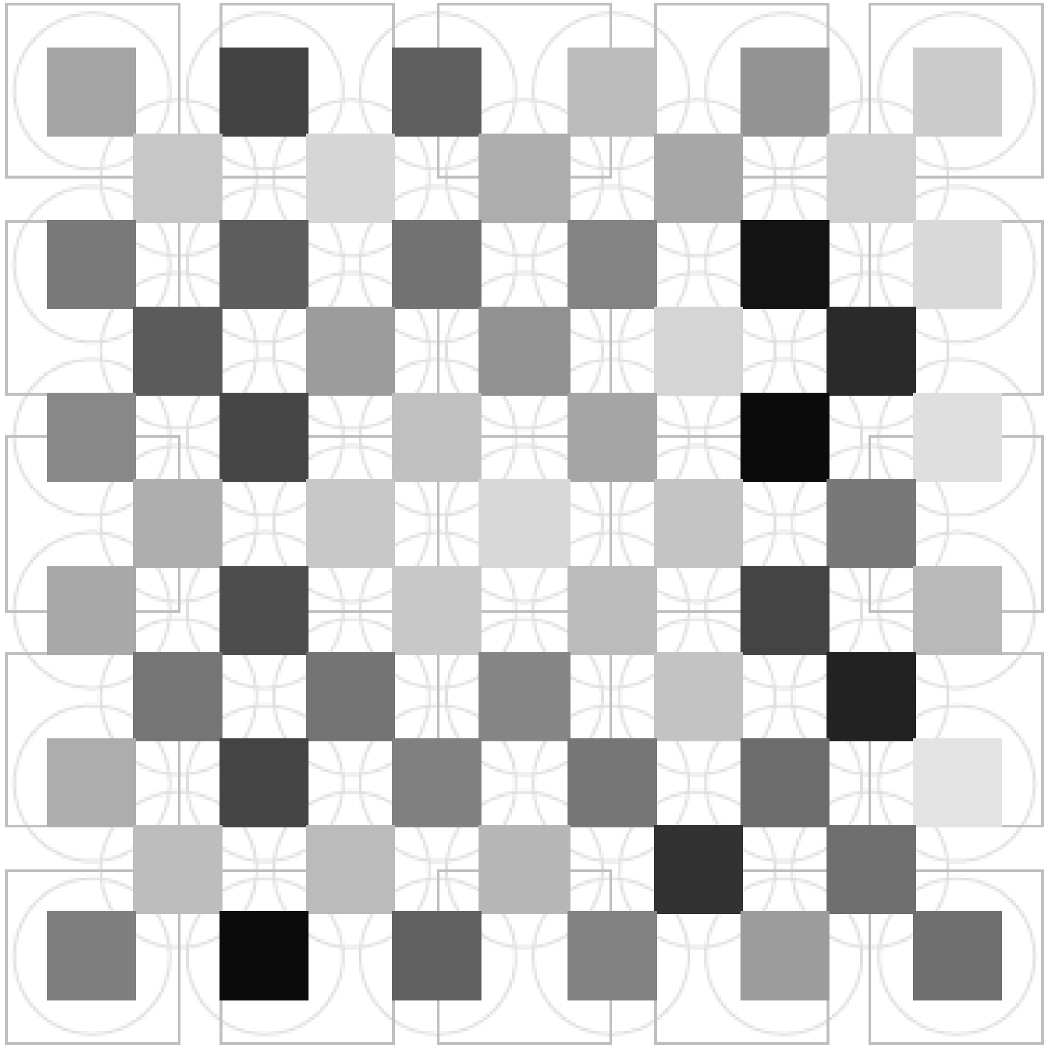


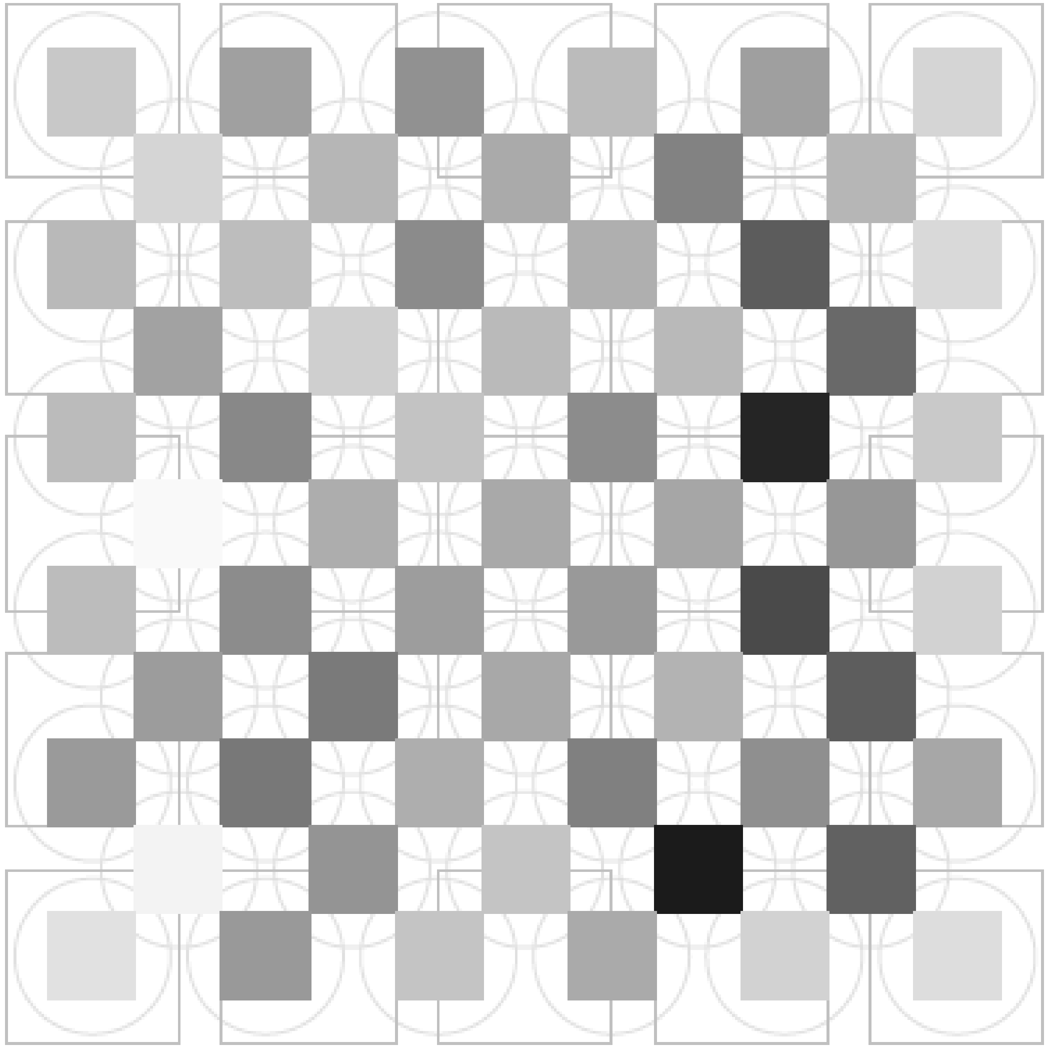
5x5



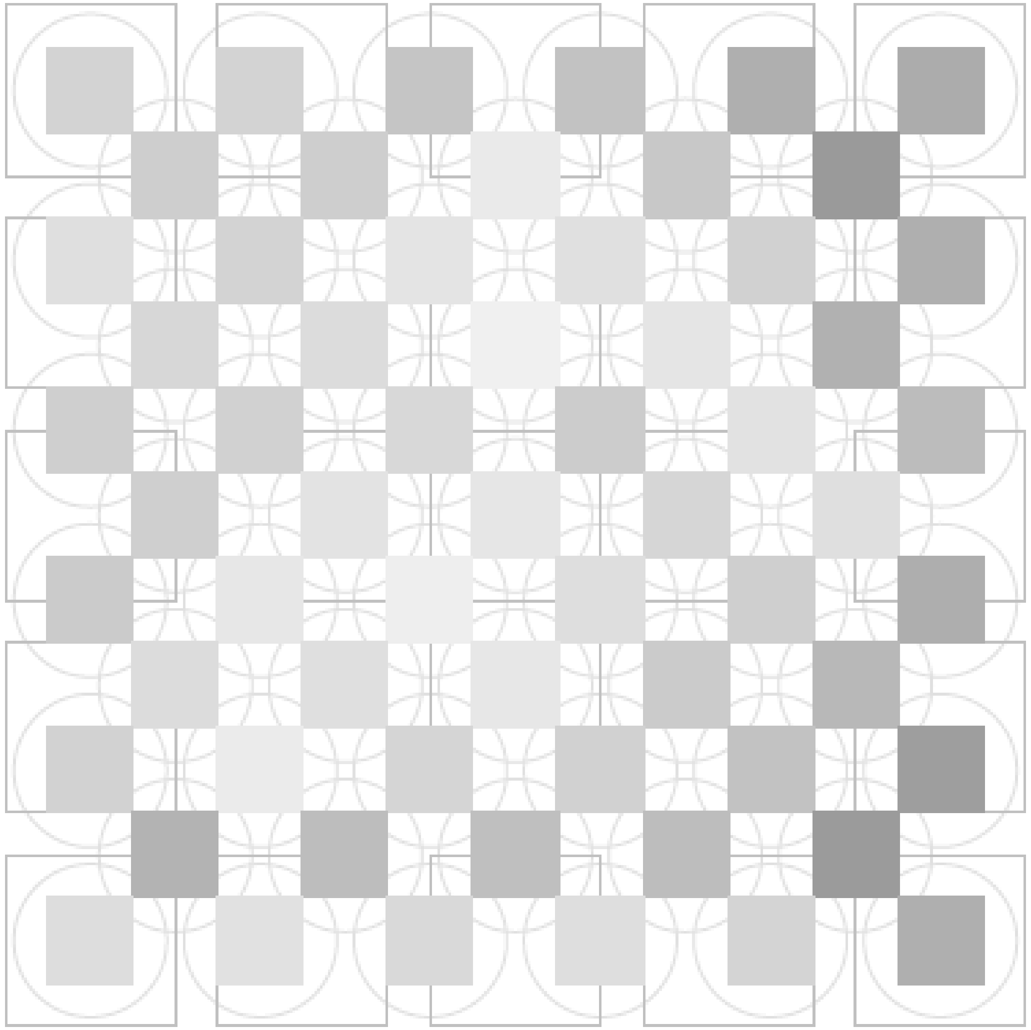
7x7

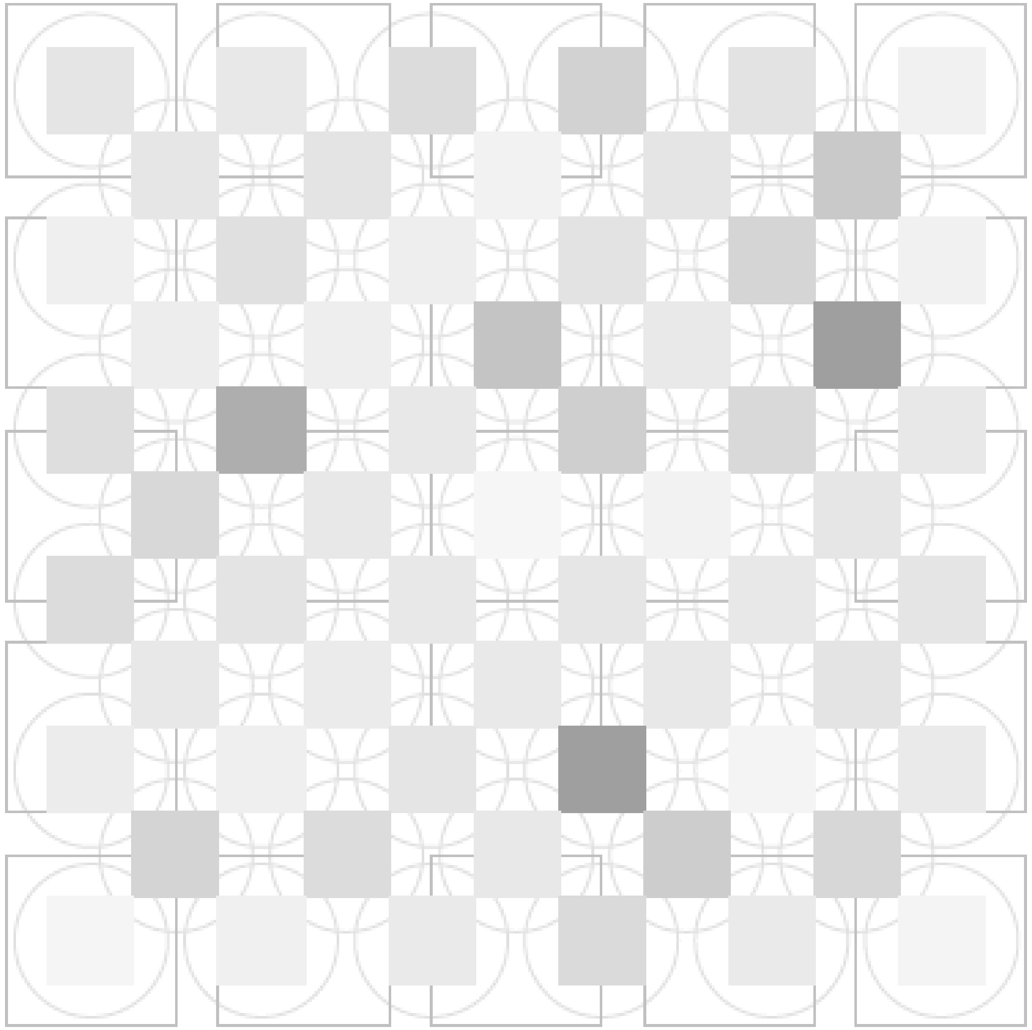
Accuracy improvement using Kadane algorithm





Precision improvement using Kadane algorithm





Thank you

Q&A – 5min

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