

Continuous unobtrusive user authentication using gait for wearable devices

utilising machine learning algorithms



Faculty of Engineering Technology

SenseID Wearable

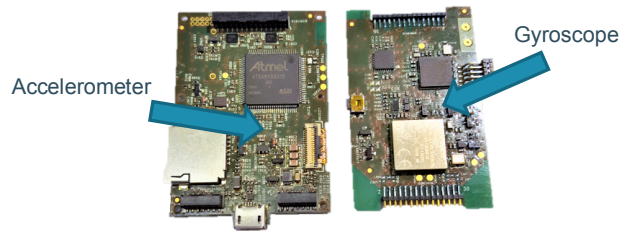
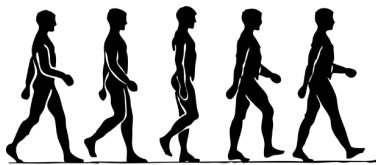
- Transparent and continuous authentication
- Wearable device packed with sensors
 - contextual data
 - biometric data

Can we develop a computationally inexpensive and accurate gait authentication model for mobile devices?



SenseID for Authentication

- Gait: “Locomotion achieved through the movement of human limbs.”
- Walking



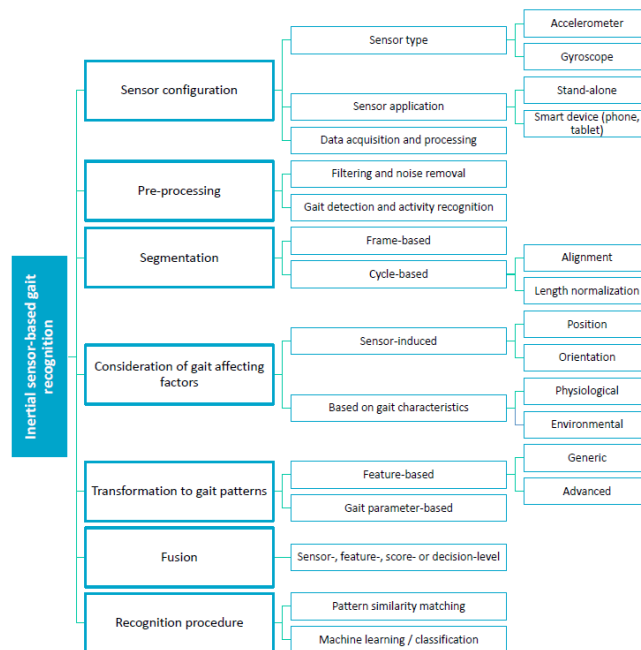
Previous work

- Walk Detector
gait **detection**
- Authentication
gait **recognition**



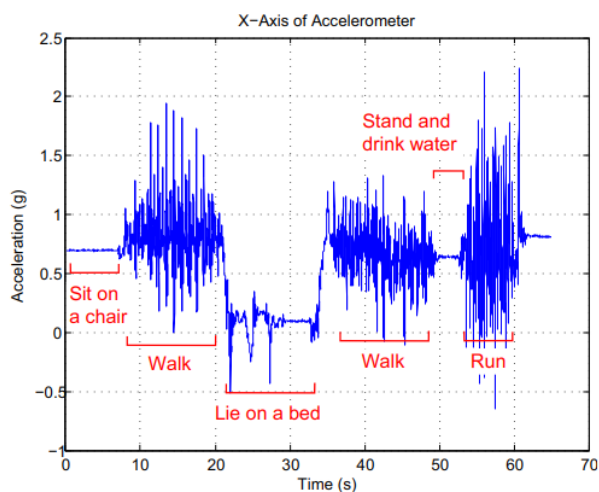
State-of-the-art gait recognition

- Sensor configuration
- Pre-processing
- Segmentation
- Feature-based
- Fusion
- Machine learning



State-of-the-art HAR (Human Activity Recognition)

- gait **detection**
- Similar methods to gait recognition
- Machine learning



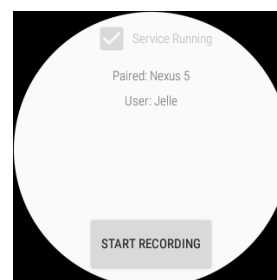
Data Collection Procedure

- Accelerometer and Gyroscope data collected from Android LG Urbane Smartwatch
- Subjects were asked to do the following:
 - 10 minutes
 - Ordinary manner
 - Straight line
 - Repeated over few days



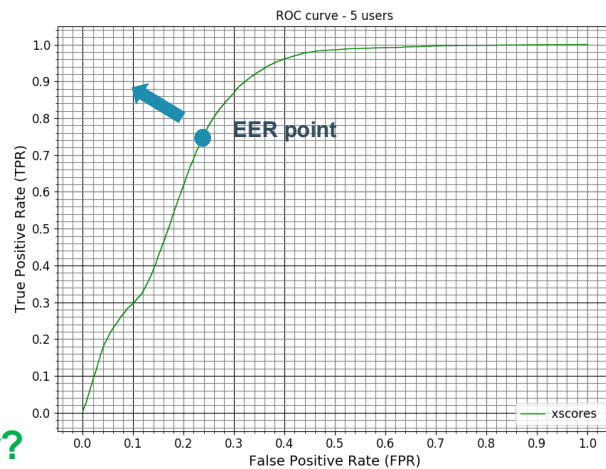
Initial Implementation (1)

- Wearable application (Android)
 - Capture Accelerometer + Gyroscope data
 - Save data to SD Card
- Server application (Python)
 - Processing
 - Train walk detector + authentication model
 - Inference models



Initial Implementation (2)

- Model for Walk Detection
- Model for Authentication
- Logistic Regression model

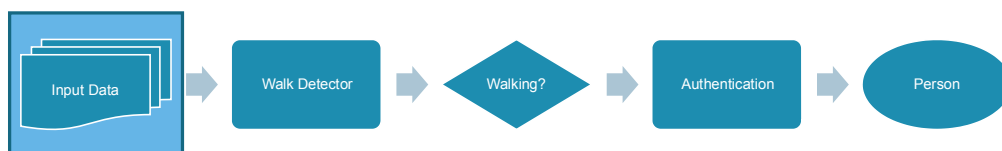


Can we improve further?

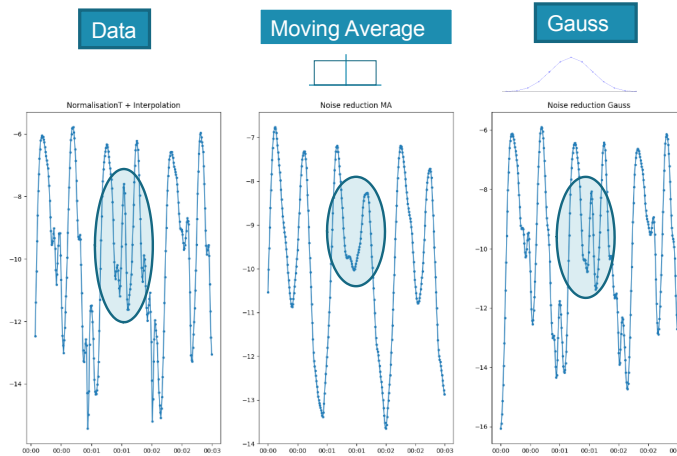
TPR: True Positive Rate EER: Equal Error Rate
TNR: True Negative Rate

Machine Learning for Gait Authentication

- Walk Detector (gait detection)
- Authentication Model (gait recognition)

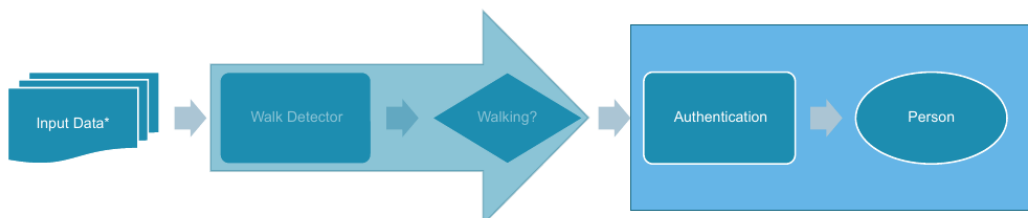


Data Filtering for Noise Removal

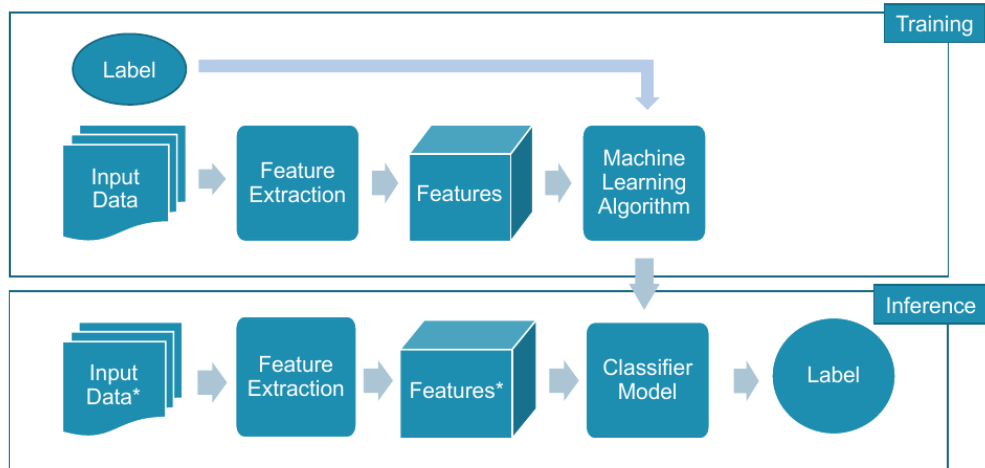


Machine Learning for Gait Authentication

- Walk Detector (gait detection)
- Authentication Model (gait recognition)



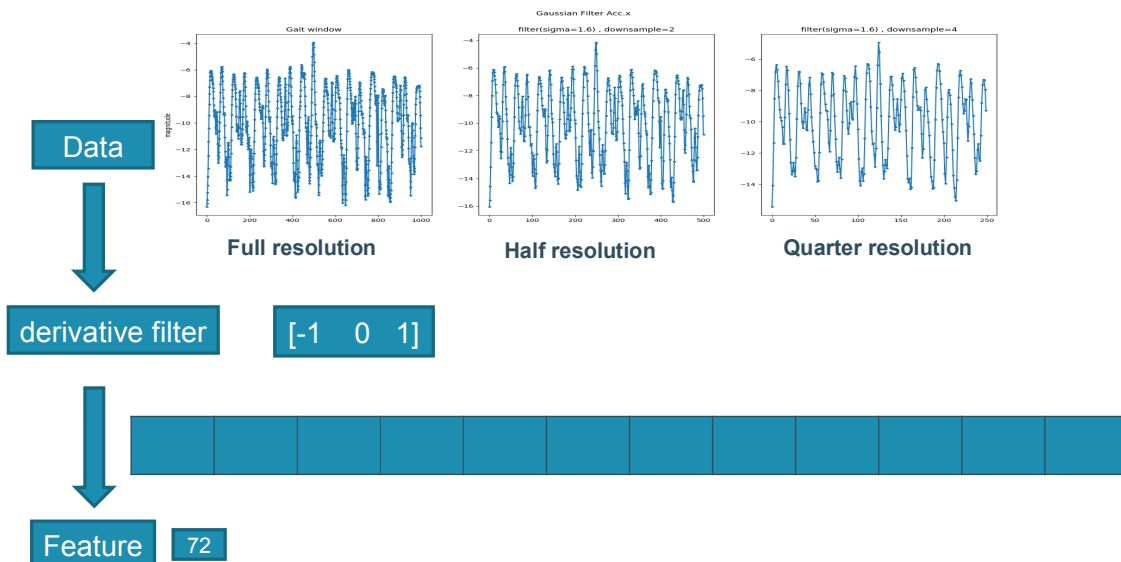
Machine Learning components



13

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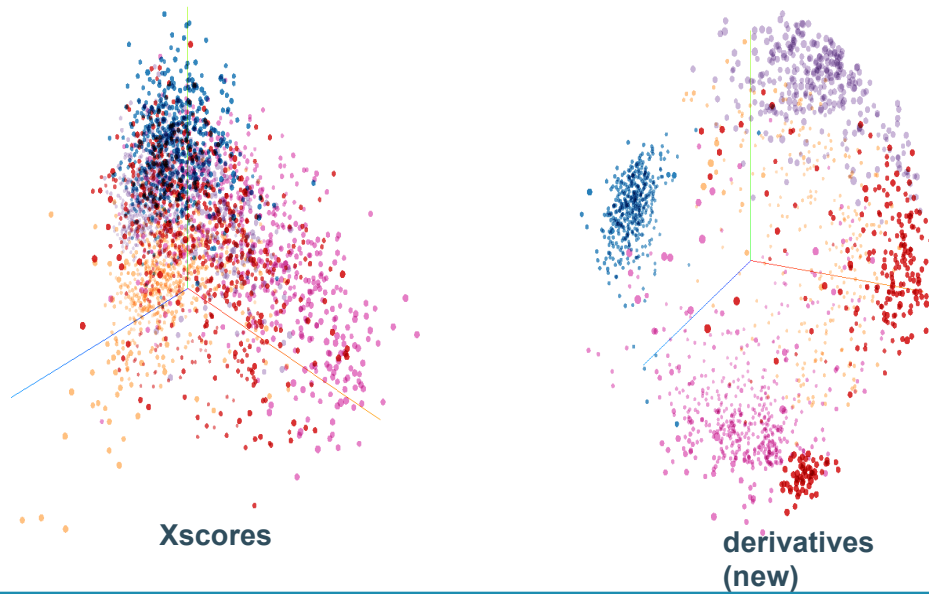
New Feature: Derivatives



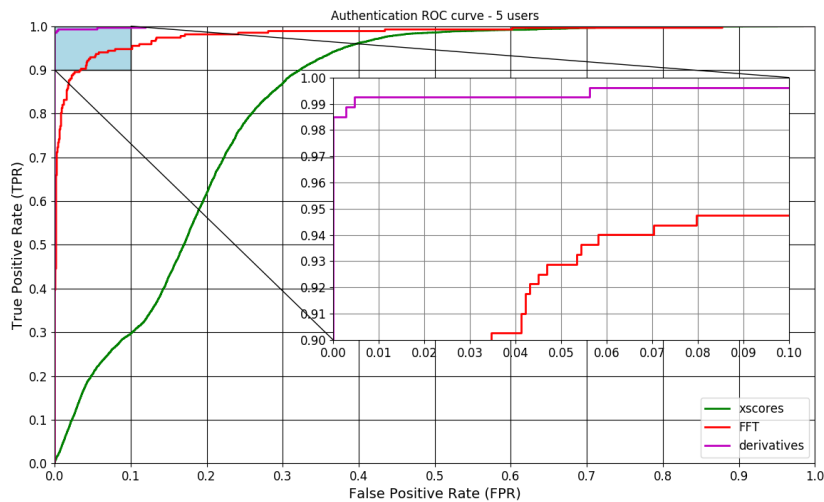
14

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Feature visualization with PCA: three principle components



ROC Graph Authentication Results

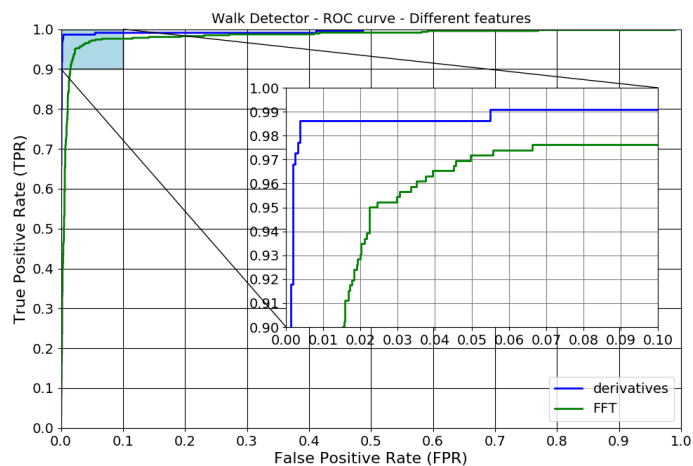


Machine Learning for Gait Authentication

- Walk Detector (gait detection)
- Authentication Model (gait recognition)



ROC Graph Walk Detector



Feature Computation time

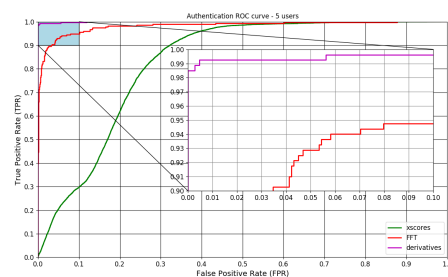
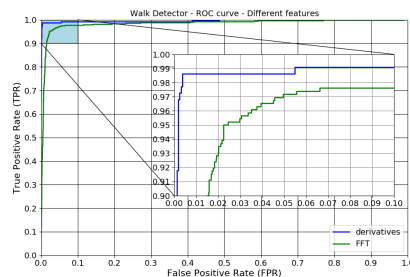
Feature	Preprocessing (ms)	Feature Computation on WD+Auth (ms)	Predict WD+Auth (ms)	Total (ms)
Xscores	13.5	724	0.4	817.9
derivative (current)	11	26	0.4	37.4

Intermediate Conclusion

- Accuracy improvement (TPR: 83.0%, TNR: 90.1%) to EER < 1%
- Speed improvement: 540ms to 13ms

Representative?

Accurate?



Validation on public datasets

- Walk Detector (gait **detection**)
HAR (Human Activity Recognition)
- Authentication Model (gait **recognition**)
Representative dataset: **51 users**

	Gait detection	Gait recognition
Size	>=5	>=50
Sensors	accelerometer and/or gyroscope	
Hardware	smartwatch, smartphone	
Position	wrist, front pocket, hip	
Duration	1 minute per activity	5 minutes
Activity	sitting, lying, standing, walking	walking

Datasets

- Gait detection: PAMAP2, USC-HAD
- Gait recognition: IDNet

Dataset	IDNet [1]	Z-JU [29]	PAMAP2 [3]	G. Wu [30]	USC-HAD [2]
Sensors	both	only accelerometer	both	both	both
Position	front pocket	wrist+others	wrist+others	fingertip	hip
Duration	>5 minutes	1 minute	5 minutes	>5 minutes	>5 minutes
Activity	walking	walking	multiple	multiple	multiple
Conditions	some outside	inside	some outside	inside	inside
Subjects	50	175	9	40	14

Validation

- Walk Detector (gait detection)
- Authentication Model (gait recognition)



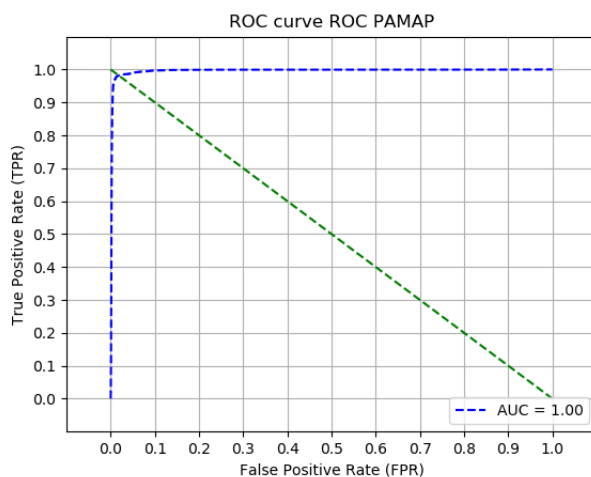
Gait detection PAMAP2

Train

Test

	subject101	subject102	subject103	subject104	subject105	subject106	subject107	subject108	subject109	Sum	Nr. of subjects
1 – lying	271.86	234.29	220.43	230.46	236.98	233.39	256.1	241.64	0	1925.15	8
2 – sitting	234.79	223.44	287.6	254.91	268.63	230.4	122.81	229.22	0	1851.8	8
3 – standing	217.16	255.75	205.32	247.05	221.31	243.55	257.5	251.59	0	1899.23	8
4 – walking	222.52	325.32	290.35	319.31	320.32	257.2	337.19	315.32	0	2387.53	8
5 – running	212.64	92.37	0	0	246.45	228.24	36.91	165.31	0	981.92	6
6 – cycling	235.74	251.07	0	226.98	245.76	204.85	226.79	254.74	0	1645.93	7
7 – Nordic walking	202.64	297.38	0	275.32	262.7	266.85	287.24	288.87	0	1881	7
9 – watching TV	836.45	0	0	0	0	0	0	0	0	836.45	1
10 – computer work	0	0	0	0	1108.82	617.76	0	687.24	685.49	3099.31	4
11 – car driving	545.18	0	0	0	0	0	0	0	0	545.18	1
12 – ascending stairs	158.88	173.4	103.87	166.92	142.79	132.89	176.44	116.81	0	1172	8
13 – descending stairs	148.97	152.11	152.72	142.83	127.25	112.7	116.16	96.53	0	1049.27	8
16 – vacuum cleaning	229.4	206.82	203.24	200.36	244.44	210.77	215.51	242.91	0	1753.45	8
17 – ironing	235.72	288.79	279.74	249.94	330.33	377.43	294.98	329.89	0	2386.82	8
18 – folding laundry	271.13	0	0	0	0	217.85	0	236.49	273.27	998.74	4
19 – house cleaning	540.88	0	0	0	284.87	287.13	0	416.9	342.05	1871.83	5
20 – playing soccer	0	0	0	0	0	0	0	181.24	287.88	469.12	2
24 – rope jumping	129.11	132.61	0	0	77.32	2.55	0	88.05	63.9	493.54	6
Labeled total	4693.07	2633.35	1743.27	2314.08	4117.97	3623.56	2327.63	4142.75	1652.59	27248.27	
Total	6957.67	4469.99	2528.32	3295.75	5295.54	4917.78	3135.98	5884.41	2019.47	38504.91	

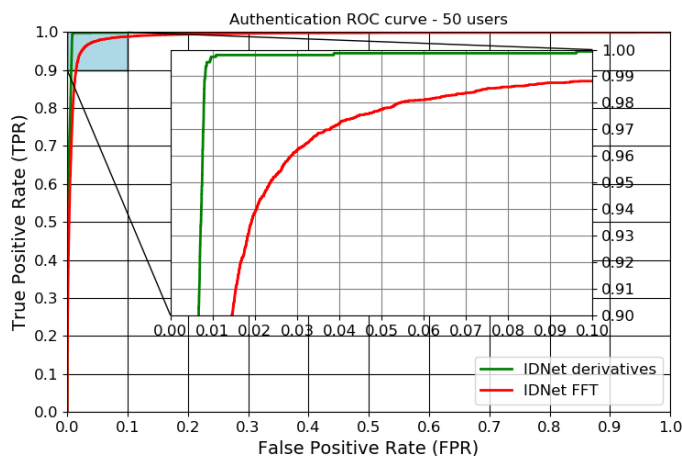
Results on PAMAP2 dataset



Gait recognition IDNet

- 50 subjects
- period of six months
- Android smartphones in front pocket
- Several sessions of five minutes were performed for each subject
- variable conditions, mimic real world scenarios

Results on IDNet



Conclusion and Future Work

- **Can we develop a computationally inexpensive and accurate gait authentication model for mobile devices?**
- SenseID wearable
 - Multiple devices
 - Realistic