Detecting Drinking Behavior in Social Settings Using Chest-Mounted Accelerometer Data

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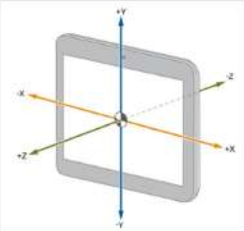
1. Introduction

- Chest-mounted accelerometers
- Analyzing annotation
- Conflab dataset
- Random forest model



Directions of an accelerometer[1]

2. Research question

How accurately can chest-mounted accelerometer data detect drinking events in natural social environments based on a random forest model?

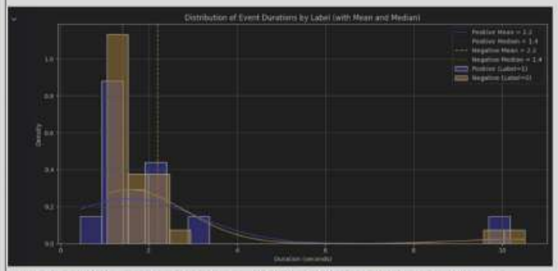
Sub questions:

- How well does a machine learning model perform in detecting drinking for a single individual?
- How well does a machine learning model perform in detecting drinking between multiple participants?
- In what cases does the machine learning model fail, and how can this be explained by studying video material?

3. Related Work

- Real-time drink trigger detection in free-living conditions using inertial sensors. (Gomes et al.) [2]
- Human Activity Recognition from an Accelerometer on The Chest: Data Transformation, Feature Selection, and Classification Performance. (Hosseinian et al.) [3]
- A Human Activity Recognition Dataset for Machine Learning. (Logacjov et al.) [4]
- A comprehensive study of activity recognition using accelerometers.(Twomey et al.)[5]

4. Method



Distribution of samples. (Blue 14 positive samples, Yellow 28 negative samples)

Component	Why It Is Used
Mean	Shows average intensity of drinking movement, which helps to detect the posture of a person when they are drinking or not drinking.
Correlation	Captures the degree to which two axes vary together over the time of the movement.
Maximum	Captures extremes of movements, which can help identify drinking.
Minimum	Captures extremes of movements, which can help identify drinking.
Covariance	Captures the degree to which two axes vary together.

Table of features used and why. (Used in y- and z-direction)

- Model is performed on data of one participant with sixfold cross-validation.
- Model is performed across participants with leave one out cross-validation.
- False positives and false negatives are studied in video material.

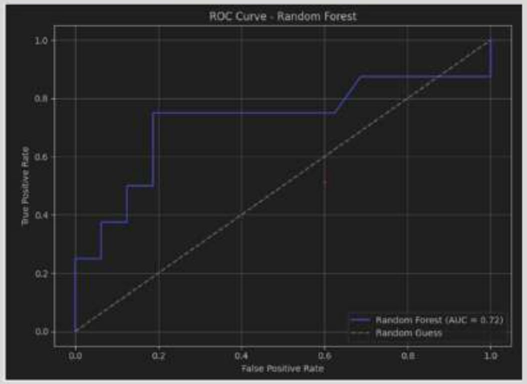
5. Result

Fold No.	Class 0				Class 1				Accuracy	Macro Avg				Weighted Avg			
	Prec.	Rec.	F1-score	Supp.	Prec.	Rec.	F1-score	Supp.		Prec.	Rec.	F1-score	Supp.	Prec.	Rec.	F1-score	Supp.
1	1.00	1.00	1.00	3	1.00	1.00	1.00	1	1.00	1.00	1.00	1.00	4	1.00	1.00	1.00	4
2	1.00	0.67	0.80	3	0.50	1.00	0.67	1	0.75	0.75	0.83	0.73	4	0.88	0.75	0.77	4
3	0.50	0.50	0.50	2	0.50	0.50	0.50	2	0.50	0.50	0.50	0.50	4	0.50	0.50	0.50	4
4	1.00	1.00	1.00	2	1.00	1.00	1.00	2	1.00	1.00	1.00	1.00	4	1.00	1.00	1.00	4
5	0.67	0.67	0.67	3	0.00	0.00	0.00	1	0.50	0.33	0.33	0.33	4	0.50	0.50	0.50	4
6	1.00	1.00	1.00	3	1.00	1.00	1.00	1	1.00	1.00	1.00	1.00	4	1.00	1.00	1.00	4
Mean	**0.86**	**0.81**	**0.83**	**2.67**	**0.67**	**0.75**	**0.69**	**1.33**	**0.79**	**0.76**	**0.78**	**0.76**	**4.00**	**0.81**	**0.79**	**0.79**	**4.00**

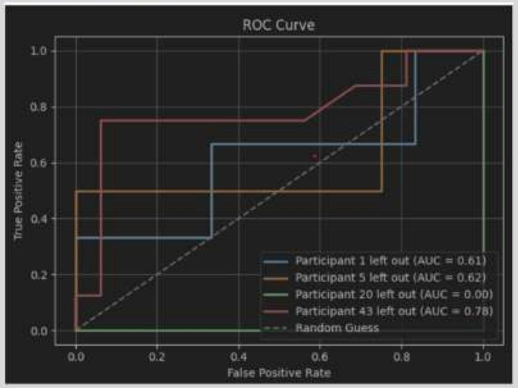
Classification report of sixfold cross-validation on one participant

Part No.	Class 0				Class 1				Accuracy	Macro Avg				Weighted Avg			
	Prec.	Rec.	F1-score	Supp.	Prec.	Rec.	F1-score	Supp.		Prec.	Rec.	F1-score	Supp.	Prec.	Rec.	F1-score	Supp.
1	0.80	0.67	0.73	6	0.50	0.67	0.57	3	0.67	0.65	0.67	0.65	9	0.70	0.67	0.68	9
5	0.80	1.00	0.89	4	1.00	0.50	0.67	2	0.83	0.90	0.75	0.78	6	0.87	0.83	0.81	6
20	0.67	1.00	0.80	2	1.00	0.00	0.00	1	0.67	0.83	0.50	0.40	3	0.78	0.67	0.53	3
43	0.82	0.56	0.67	16	0.46	0.75	0.57	8	0.62	0.64	0.66	0.62	24	0.70	0.62	0.63	24
Mean	**0.77**	**0.81**	**0.77**	**7.00**	**0.74**	**0.48**	**0.45**	**3.50**	**0.70**	**0.76**	**0.65**	**0.61**	**10.50**	**0.76**	**0.70**	**0.66**	**10.50**

Classification report of leave one out cross-validation across participants



ROC curve one participant sixfold CV



ROC curve across participants LOOCV

5. Result (Continued)

Qualitative analysis

- False negative (one participant): Walking and drinking at the same time is hard to predict.
- False positive (one participant): nodding during conversation is predicted as drinking.
- False positive (across participants): Movement of drinking hand is hard to predict.

6. Conclusion

- Sixfold cross-validation on one participant shows causation between accelerometer data statistical features and drinking.
- Drinking behavior is predictable across participant, but harder than for one participant.
- Qualitative analysis shows possible improvement in model by labeling current prediction errors in model.
- Random forest model predicts already decently for conflab dataset, but more data and better labeling can still improve current models. Whether it can perform as well as arm mounted accelerometers can not be concluded

7. References

[1] Accelerometer - Measure linear acceleration along X, Y, and Z axes in m/s2 - Simulink.

[2] Diana Gomes and In^es Sousa. Real-time drink trigger detection in free-living conditions using inertial sensors. Sensors, 19(9), 2019.

[3] Seyed Mohammadreza Hosseinian. Human Activity Recognition from an Accelerometer on The Chest: Data Transformation, Feature Selection, and Classification Performance. December 2017.

[4] Aleksej Logacjov, Kerstin Bach, Atle Kongsvold, Hilde Bremseth B˚ardstu, and Paul Jarle Mork. HARTH: A Human Activity Recognition Dataset for Machine Learning. Sensors (Basel, Switzerland), 21(23):7853, November 2021.

[5] Niall Twomey, Tom Diethe, Xenofon Fafoutis, Atis Elsts, Ryan McConville, Peter Flach, and Ian Craddock. A comprehensive study of activity recognition using accelerometers. Informatics, 5(2), 2018.