‘StopWatch’

- a smartwatch based system for passive detection of cigarette smoking

Andy Skinner, Chris Stone, Hazel Doughty, Marcus Munafò

Tobacco and Alcohol Research Group
MRC Integrative Epidemiology Unit
School of Experimental Psychology
University of Bristol

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Recent quote…

"The act of smoking can already be identified using a wrist-worn accelerometer, and it may soon be possible with off-the-shelf smart watches"

Naughton, F (2017)
Delivering "Just-In-Time" smoking cessation support via mobile phones: current knowledge and future directions
Nicotine and Tobacco Research, 19(3), 379-383

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Outline

- Background to the project
- Development and testing of the smartwatch system
- Results / performance metrics

Project aim

- Use commercially-available wearable technology devices to monitor and detect lifestyle health behaviours and capture data about the way people lead their lives

- Utilise motion sensors built into the wearable device, to look for particular patterns of hand movement that are the motion signature of activities such as smoking or eating

- Measure performance of the device in a controlled laboratory environment, and compare it with performance in free-living conditions in the wild

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The need for passive detection of smoking

- Self-reporting is unreliable…

- Self-reports of number of cigarettes smoked each day show under-reporting

  - Hatziandreu EJ, Pierce JP, Fiore MC et al (1989)
    The reliability of self-reported cigarette consumption in the United States
    American Journal of Public Health, 79(8):1020-1023

  - Krall E, Valadian I, Dwyer JT, Gardner J (1989)
    Accuracy of recalled smoking data
    American Journal of Public Health, 79(8):200-206

- especially where there is a high demand for abstinence (e.g. cardiac patients, pregnant women) or for those on cessation interventions

  - Sillet RW, Wilson MB, Malcolm RE, Ball KP (1978)
    Deception among smokers.
    British Medical Journal, 2:1185-1186

  - Venditti CC, Smith GN (2012)
    Self-reported cigarette smoking status imprecisely quantifies exposure in pregnancy
    Open Journal of Obstetrics and Gynaecology, 2:56-61

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The need for passive detection of smoking

- Tendency of digit bias towards round numbers (eg. 10, 20, 30) – rounding down rather than up
  - Klesges RC, Debon M, Ray JW (1995)
    Are self-reports of smoking rate biased? Evidence from the Second National Health and Nutrition Examination Survey
    Journal of Clinical Epidemiology, 48(10):1225-1233

- Under-reporting more common amongst adolescents
  - Patrick DL, Cheadle A, Thompson DC, Diehr P, Koepsell T, Kinne S (1994)
    The validity of self-reported smoking: a review and meta-analysis
    American Journal of Public Health, 84(7):1086-1093

Why use a smartwatch to detect smoking?

- Provides the required motion sensors (inertial measurement units):
  - Accelerometer and gyroscope
- Compatible with mobile technology standards
  - Phone-based software
  - Bluetooth / USB connectivity
- Commercial product:
  - Widely available, relatively cheap
  - Reproducible environment
- Convenient and wearer-friendly format encourages user adoption and facilitates engagement with interventions

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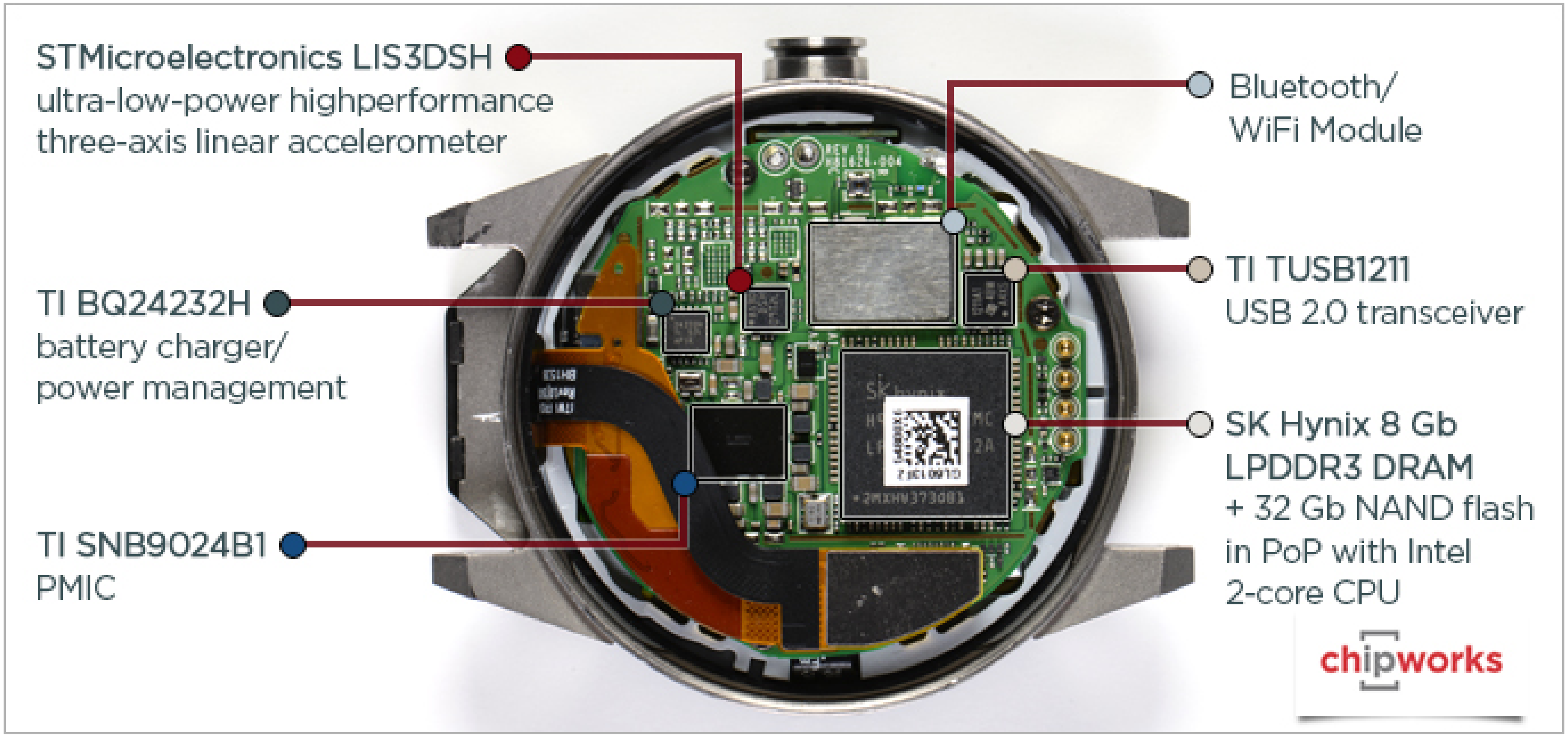
Inertial measurement units



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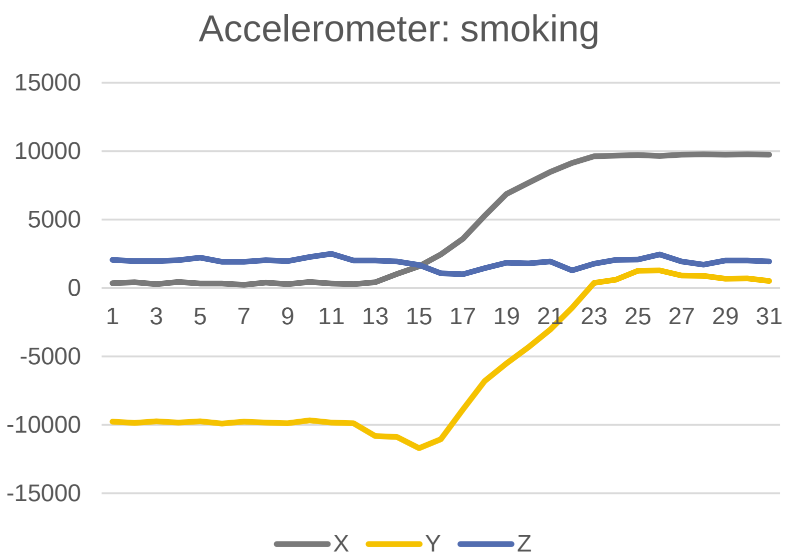
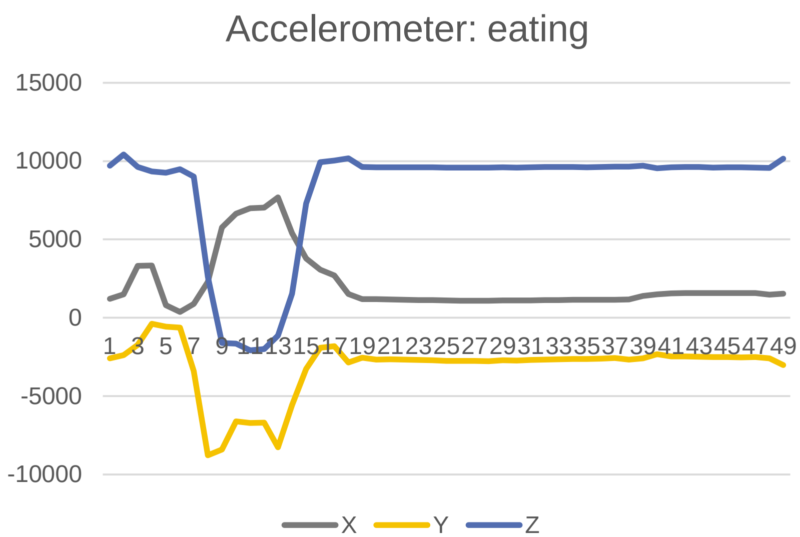
Sensor outputs during smoking vs. eating





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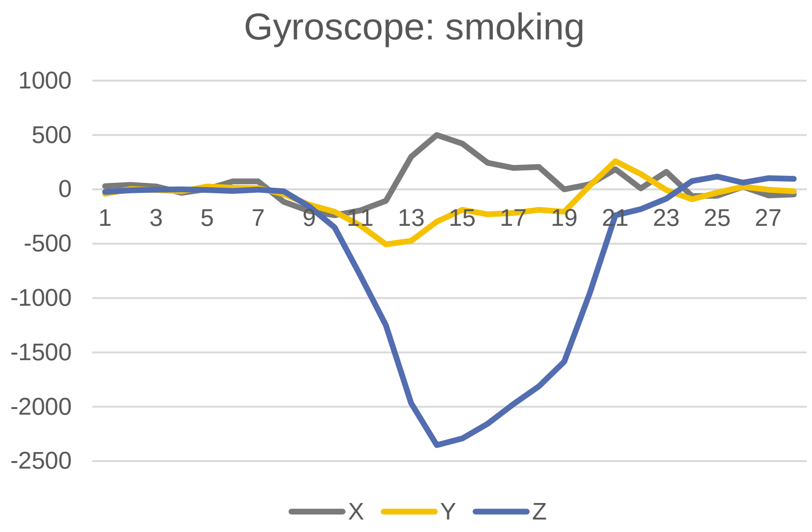
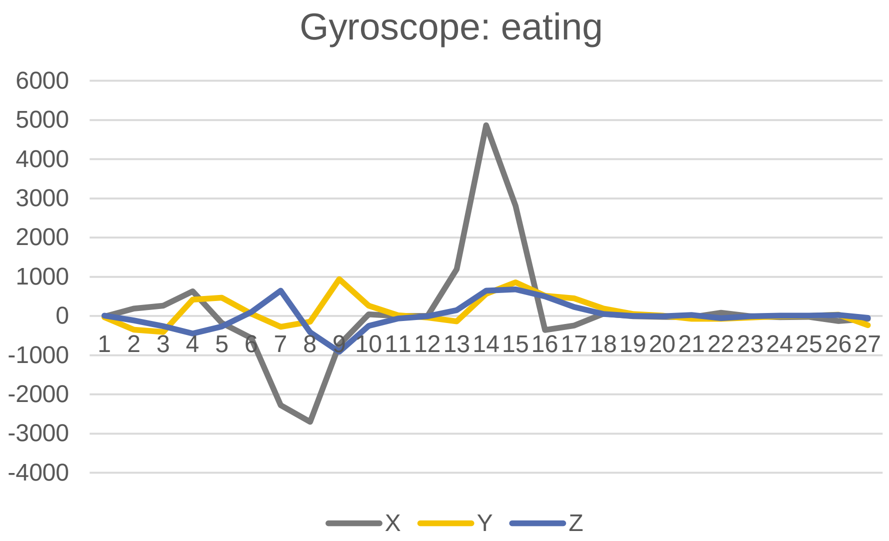
Sensor outputs during smoking vs. eating





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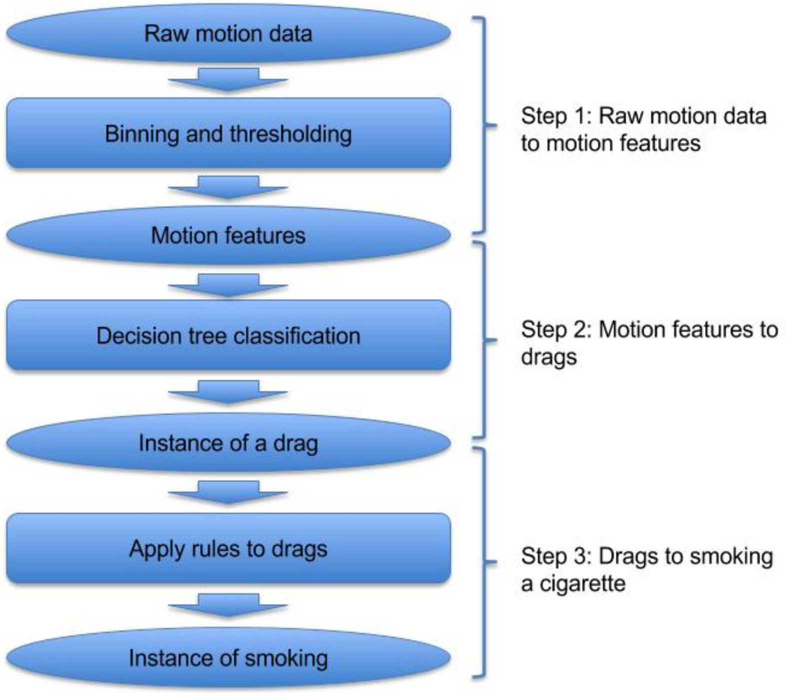
3-step analytic pipeline



Classification of motion features as drags

- Signature gesture of smoking made up of a number of movements:
- Raise hand to mouth (speed, duration)
- “Smoking position”
- Dwell time at mouth
- Move hand away from mouth (speed, duration)

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Rules to identify smoking

- Minimum of 6 drags to count as a cigarette
- 80 seconds elapsed with no further drags counts as end of cigarette
- Speed of movement; min/max dwell time for hand at mouth
- Context-based – parameters different if already smoking
- Rules based on data gathered during prototype testing

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Architecture of the app

- Android
- Java programs
  - for process control
- XML code
  - to define function of user interface screens
- Android Studio integrated development environment (IDE)
  - links source code, libraries and resources
  - coordinates build process
  - generates installation package for the app
- Android Wear operating system on the watch
- LG ‘G’ watch

Developing the app

- Prototype –
  - Raw motion data recorded on smartwatch
  - Activity ground truth data recorded manually by observer
  - Decision tree generated from raw motion & ground truth data

- Main development –
  - Extended to include in-app recording of ground truth activity
  - Analysis carried out on the watch – no need to keep raw data
  - User-friendly interface provided; database added to store results
  - Suite of programs for downloading data and refreshing the database
  - Developed and tested in phases to refine detection algorithm

Test procedure

- Initial lab session to verify detection/non-detection on sample tasks:
    - Smoking a cigarette
    - Drinking
    - Eating with fingers
    - Eating with cutlery
        - Opportunity to observe any unusual behaviour that may affect results

- Participant then wears the watch during 24 hours "in the wild"
- Watch records smoking detections
- Participant records ground truth data using the watch app
- Participant keeps a smoking diary and records incidence of smoking
- After 24 hours, follow-up session with participant for feedback

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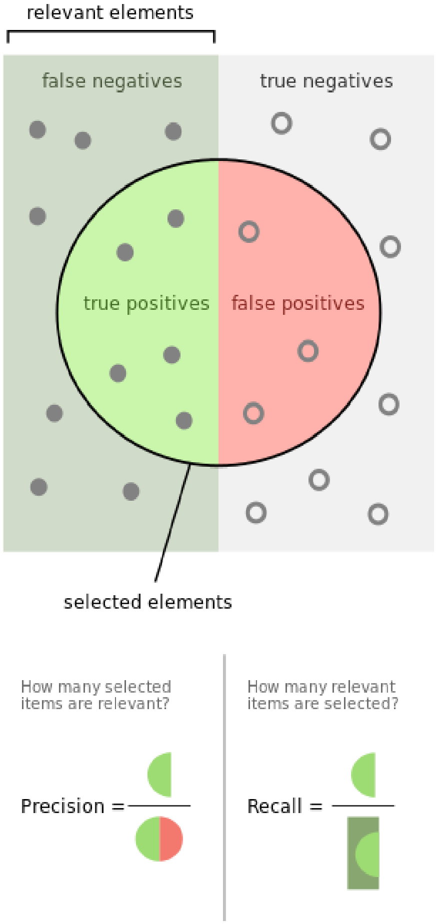
Metrics – Precision and Recall(Sensitivity)

- **Precision (Positive Predictive Value)**
  - Percentage of positive predictions that are correct
  - How many of events flagged as smoking are actual smoking events
- **Recall / Sensitivity (True Positive Rate)**
  - Percentage of positive cases that are caught/correctly classified
  - How many of the actual smoking events have been identified

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$



Results – in the lab

- Mean precision and recall/sensitivity:

Phase	Mean Precision (%)	Mean Recall (%)	n
PHASE 1 – Initial version *(apparently high precision skewed by a very small number of true positives and no false positives in the whole sample)*	100.000	28.571	7
PHASE 2 – First performance upgrade	87.500	82.353	17
PHASE 3 – Second performance upgrade	**75.000**	**92.308**	13

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Results – in the “wild”

- Mean precision and recall/sensitivity:

Phase	Mean Precision (%)	Mean Recall (%)	n
PHASE 1 – Initial version *(apparently high precision skewed by very small number of true positives and only one false positive in whole sample)*	96.222	28.222	9
PHASE 2 – First performance upgrade	83.000	62.272	11
PHASE 3 – Second performance upgrade	**85.615**	**70.461**	13

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Next steps?

- International patent applied for (January 2017)
- Potential for use in healthcare interventions – as ***Stop***Watch
  - precision intervention; “just-in-time” (context-triggered)
- Use in further studies, along with other data capture apps
  - e.g. smoking measurement alongside EMA
- Extend the concept to other lifestyle health behaviours
  - e.g. develop for drinking, chaotic eating

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Summary

- Decision tree algorithm can be used to identify smoking gestures
- Algorithm can be implemented in an app to run on a smartwatch containing standard motion sensors
- Off-the-shelf smartwatch can be used for detection of smoking
- Results:

Accuracy:	> 90%	(in lab)
Precision:	> 85%	(in the wild)
Recall:	> 70%	(in the wild)

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Recent quote…

"The potential of the vast and growing array of sensors included as standard on many smartphones, and other mobile devices such as wearables, is only just beginning to be realised"

Munafò, M (2017)
How can technology support smoking cessation interventions?
Nicotine and Tobacco Research, 19(3), 271-272

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Contact: psyc-targ@bristol.ac.uk; @BristolTARG; http://www.bristol.ac.uk/targ

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