Developing new clinical decision support tools for Parkinson's disease management

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Problem with current assessment

Physical presence in the clinic

- Cumbersome for those living in remote areas
- People need to take days off work

Limited time window

- Time consuming
- Snapshot: does not capture daily variability

No ground truth

- Subjective, depends on rater's experience
- Inter-rater variability

Quantifying symptom severity

Unified Parkinson's Disease Rating Scale (UPDRS)

comprises three components and 44 sections in total, each section spans the range 0-4

Component 1
Mentation, behavior and mood
4 sections (1-4)

Includes mentation, thought disorder, depression, and motivation/initiative

Component 2
Activities of daily living
13 sections (5-17)

Ability to complete daily tasks unassisted, e.g. dressing, walking, writing

Component 3
Motor (motor-UPDRS)
27 sections (18-44)

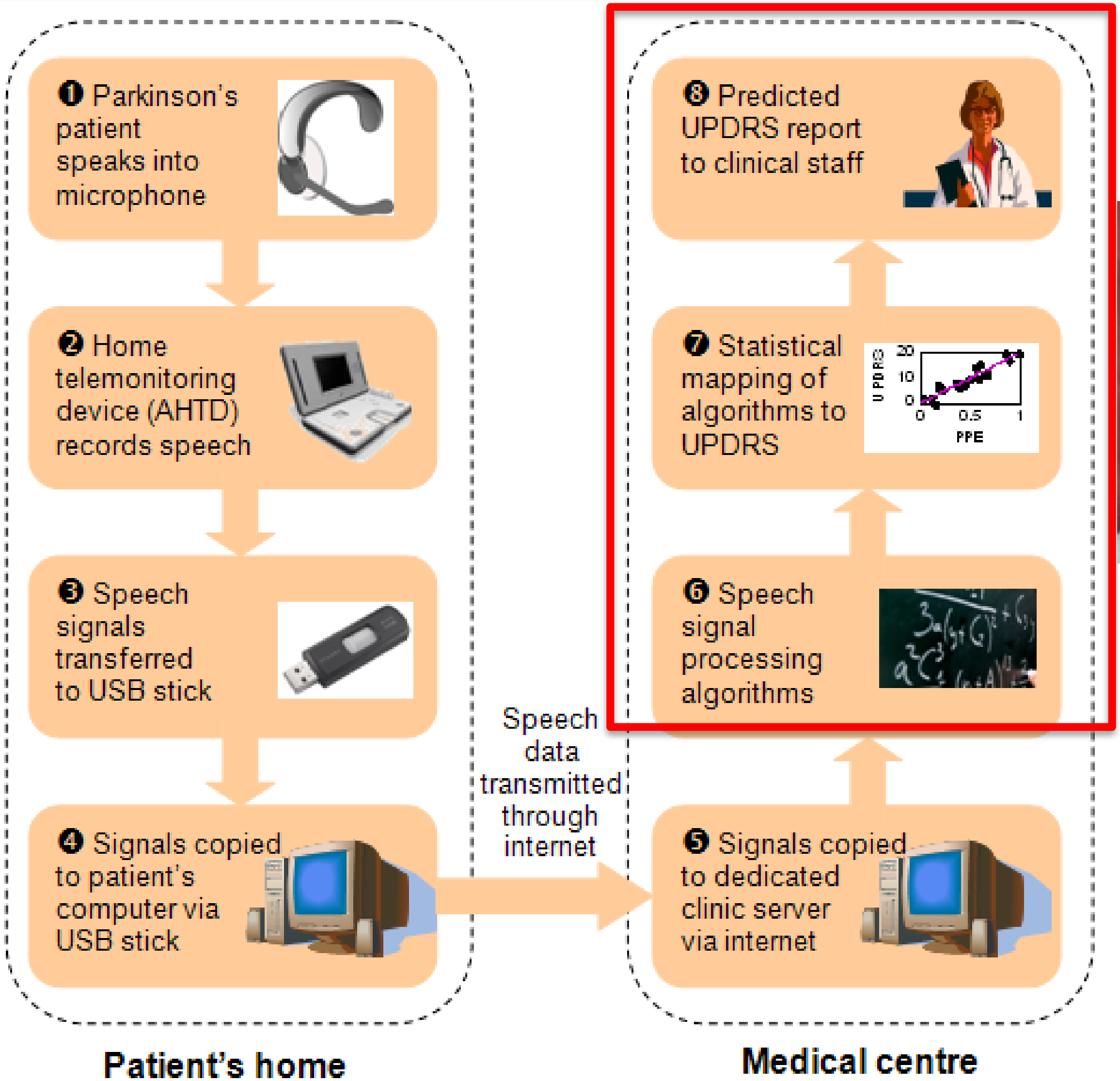
Muscle problems e.g. tremor, rigidity, posture, stability, bradykinesia

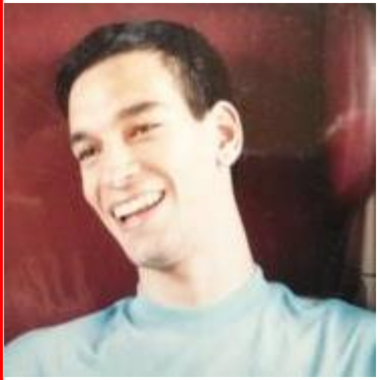
Section 5: Speech – the clinician assesses whether the subject's vocal output is *understandable* during casual discussion.

Section 18: Speech – the clinician assesses whether the subject's vocal output is *expressive* during casual discussion.

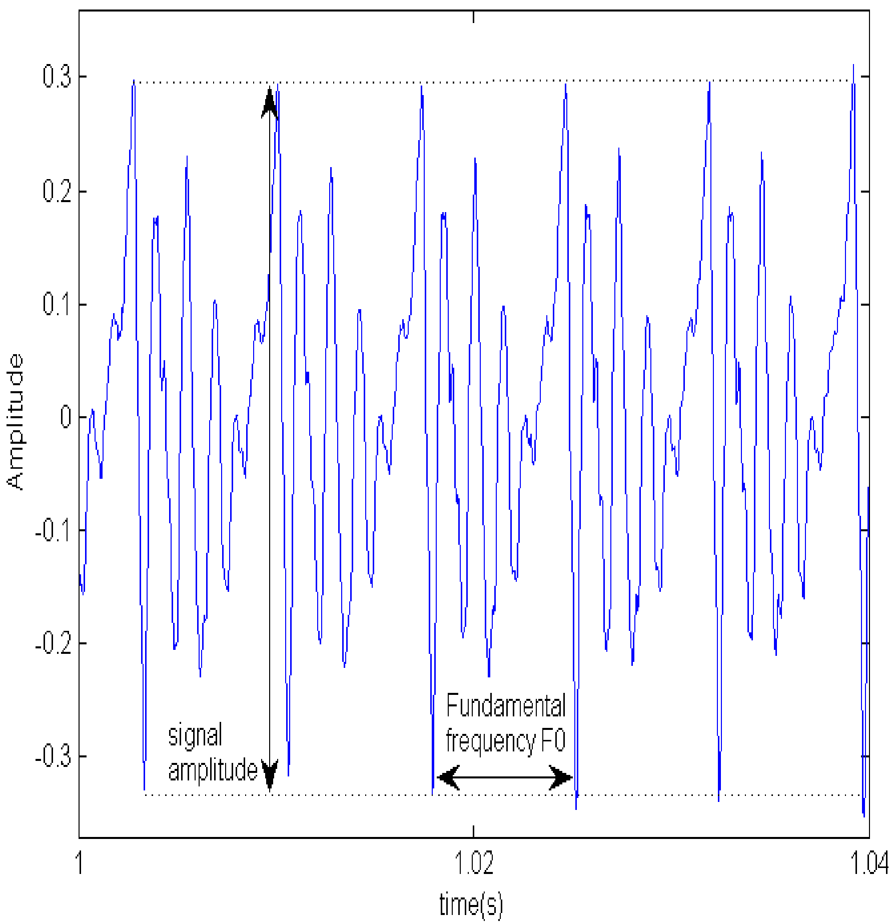
Proposed solution

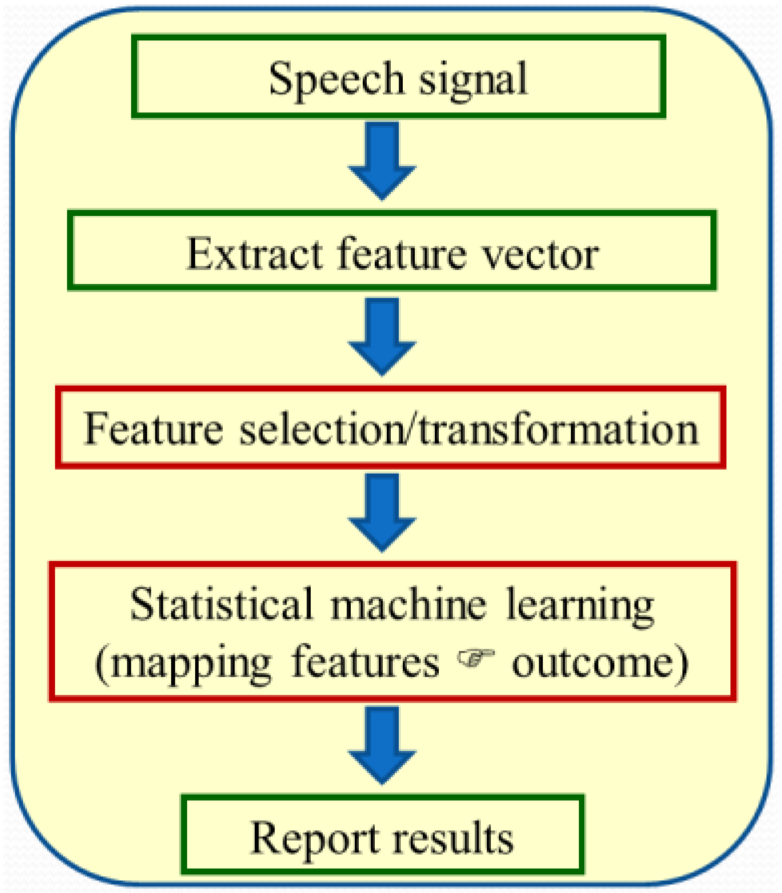
Telemedicine:
the dawn of a new era



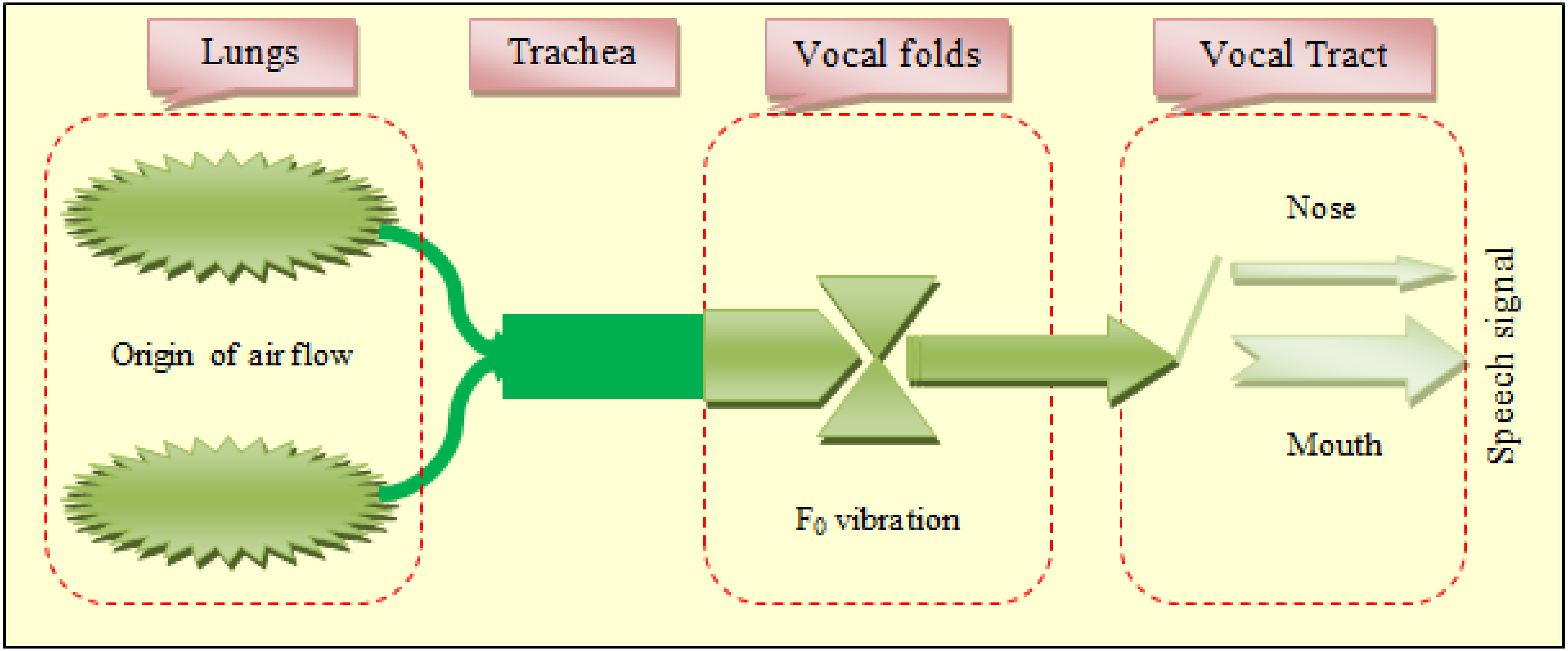


Time-series & pattern recognition

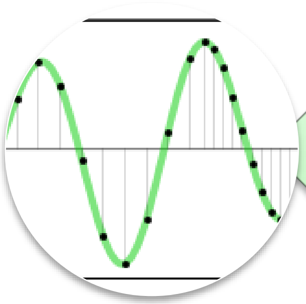




Voice production mechanism



Feature extraction

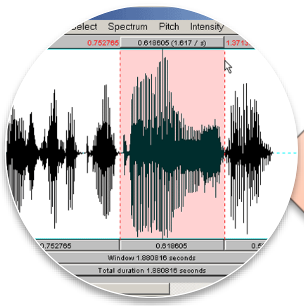


Perturbation algorithms

- Amplitude changes
- Frequency changes

Repeatability (entropy)

- Pattern consistency
- Variability



Energy

- Duration
- Signal-to-noise ratio concepts

Overview of data analysis

Feature generation from raw data → Feature selection or transformation → Statistical mapping

X | **y**

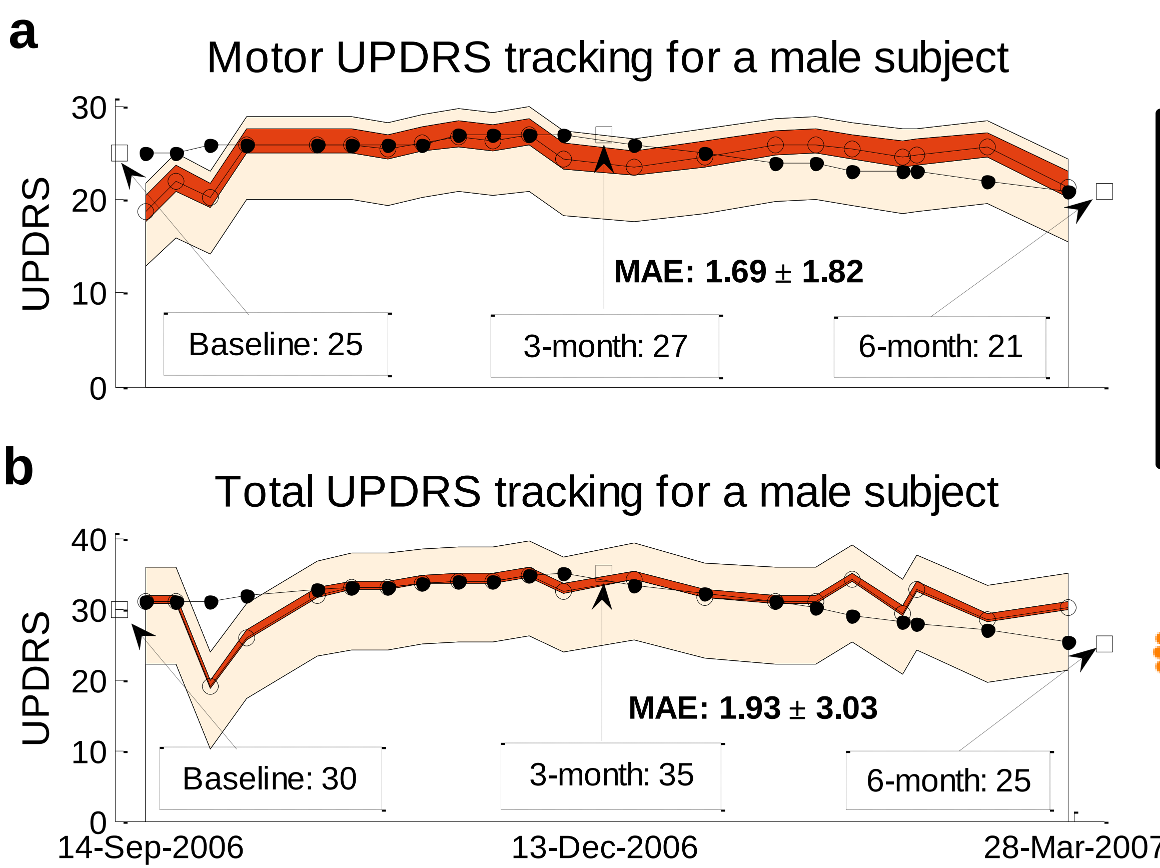
Subjects	feature1	feature2	...	feature M	result
P1	3.1	1.3		0.9	1
P2	3.7	1.0		1.3	2
P3	2.9	2.6		0.6	1
…					…
P_N	1.7	2.0		0.7	3

N (subjects)

M (features or characteristics) | outcome

- Depending on the problem, "features" can be demographics, genes, …
- $\mathbf{y} = f(\mathbf{X})$, f : mechanism **X**: feature set **y**: outcome

Remote assessment



A. Tsanas, et al., TBME 2010, JRSI 2011, TBME 2012, PRD 2012, TNSRE 2014

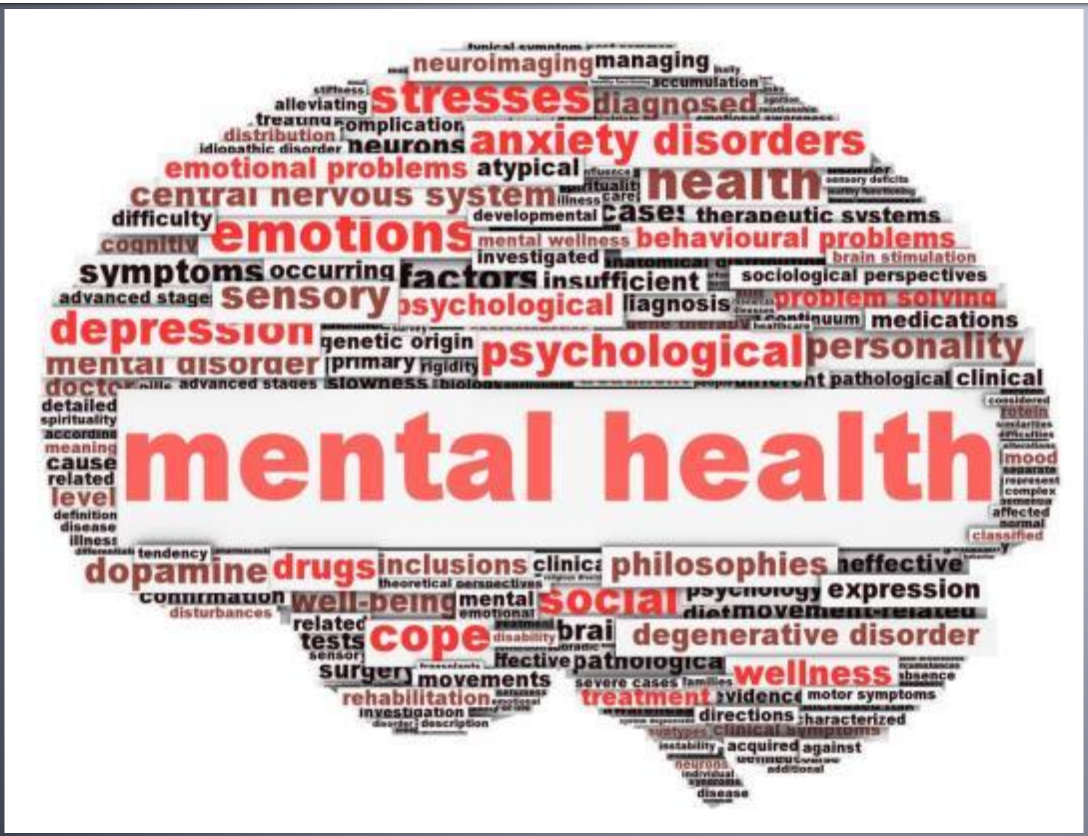
REUTERS

□ Clinicians' assessment, ● interpolated UPDRS, ○ predicted UPDRS

25-75 percentile confidence interval, 5-95 percentile confidence interval

Mental health telemonitoring

Project 2



Oxford Health NHS
NHS Foundation Trust

Problem with current assessment

Physical presence in the clinic

- Cumbersome for those living in remote areas
- People need to take days off work

Patient-led self-monitoring

- Recall bias
- Subjectivity

No ground truth

- No way to assess intervention effects
- Inter-rater variability

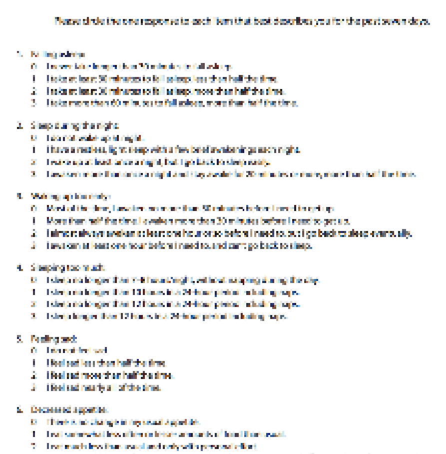
Proposed solution

- Frequent **time-stamped** self-reports

- Sensor-based **objective** monitoring

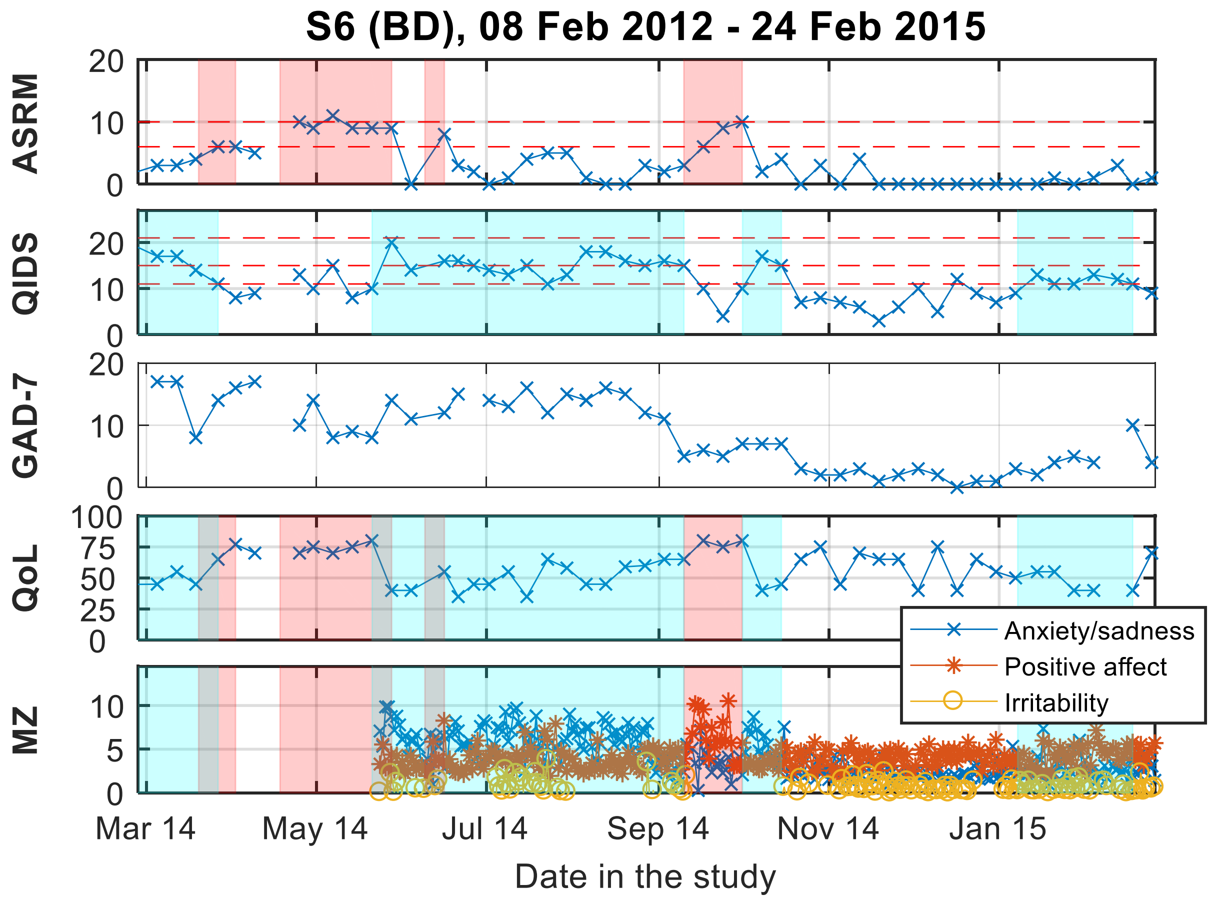
Assessing mental health

- Continuous personalized monitoring
- Objectively quantify mental health
- Identify characteristic patterns



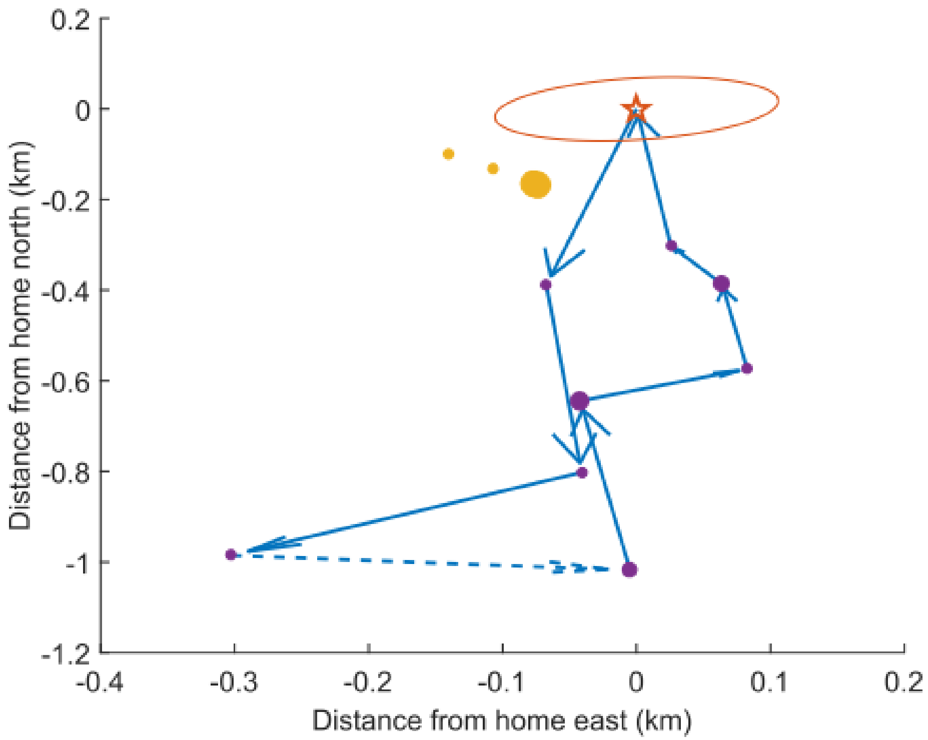
Quick Inventory of Depressive Symptomatology—Self-Report (QIDS-SR)

Self-assessment: questionnaires

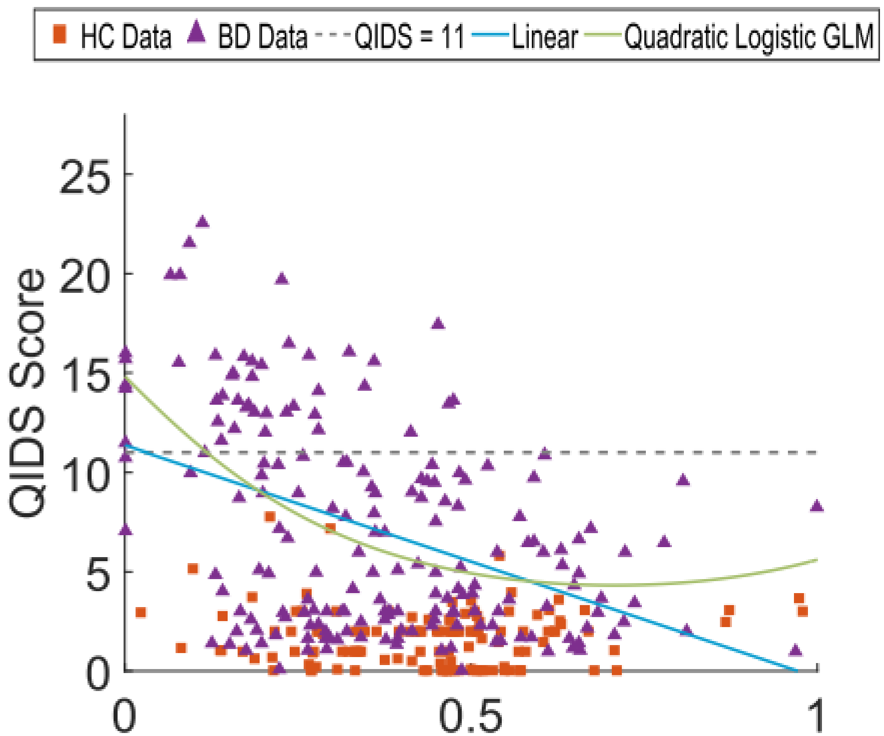


A. Tsanas et al.: Daily longitudinal self-monitoring of mood variability in bipolar disorder and borderline personality disorder**, Journal of Affective Disorders**, Vol. 205, pp. 225-233, 2016
A. Tsanas et al.: Clinical insight into latent variables of psychiatric questionnaires for mood symptom self-assessment**, JMIR Mental Health**, Vol. 4, pp. e15, 2017

Geolocation and depression



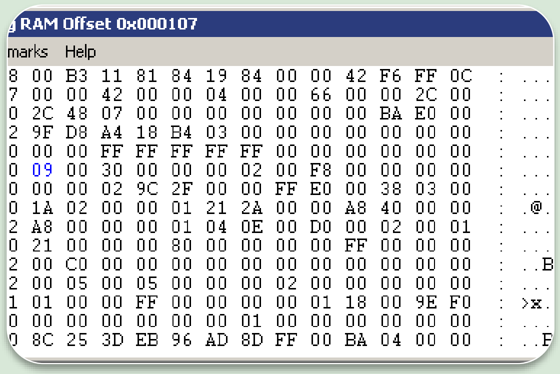
(a) Raw data coordinates with inaccurately recorded noise (weekend)

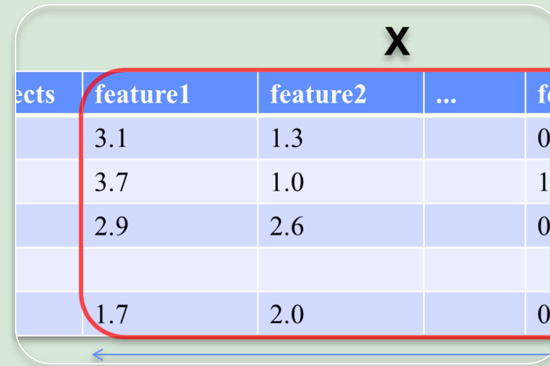


(a) Normalized entropy (weekdays)

N. Palmius, A. Tsanas, K.E.A. Saunders, A.C. Bilderbeck, J.R. Geddes, G.M. Goodwin, M. De Vos: Detecting bipolar depression from geographic location data, **IEEE Transactions on Biomedical Engineering**, Vol. 64, pp. 1761-1771, 2017

Activity, sleep, diurnal rhythm



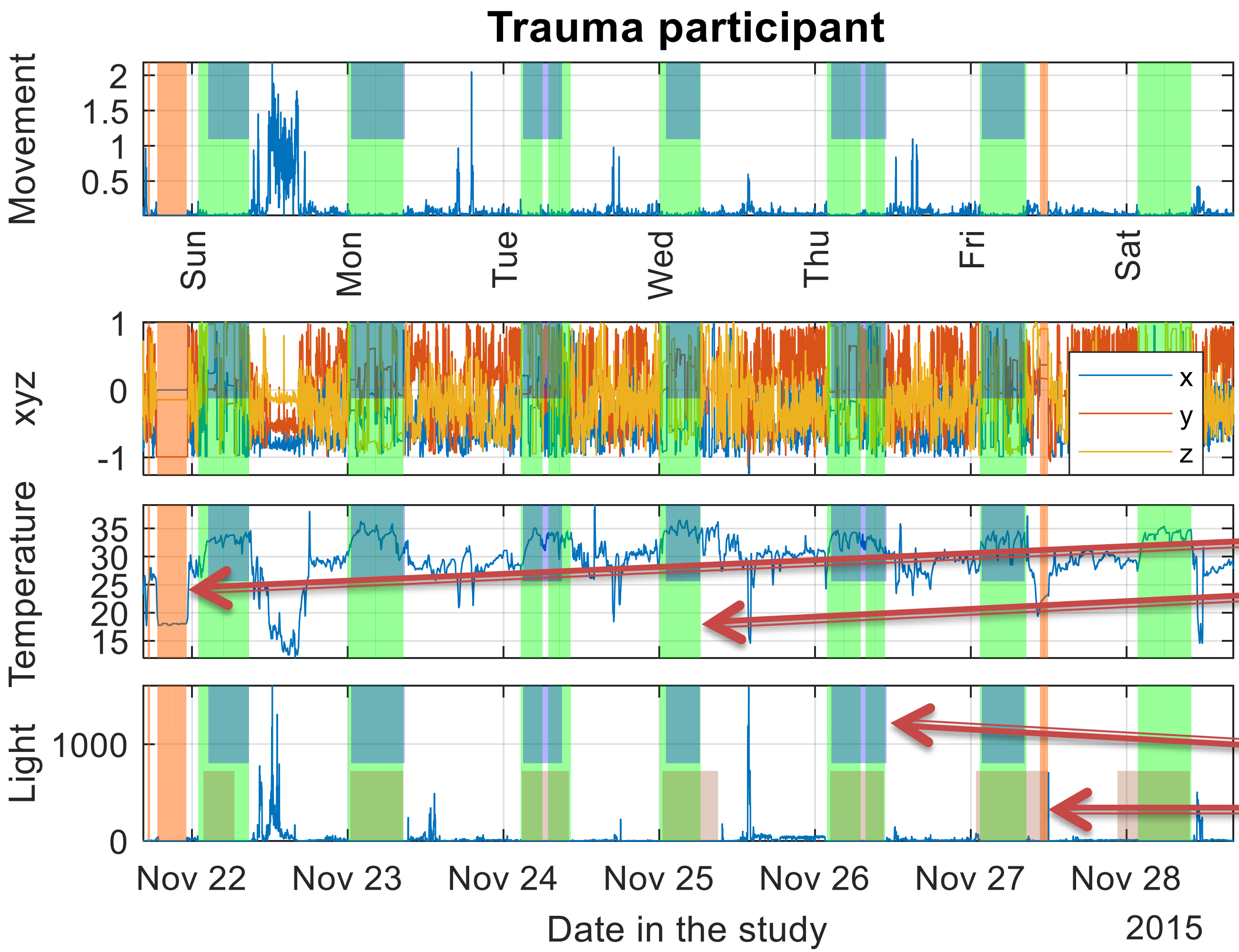


ects	feature1	feature2	...	fe
	3.1	1.3		0.
	3.7	1.0		1.
	2.9	2.6		0.
	1.7	2.0		0.

Raw data | Processed patterns | Features

Extract data → Pre-process → Characterise

Sleep detection example



Geneactiv

- Non-wear
- Asleep

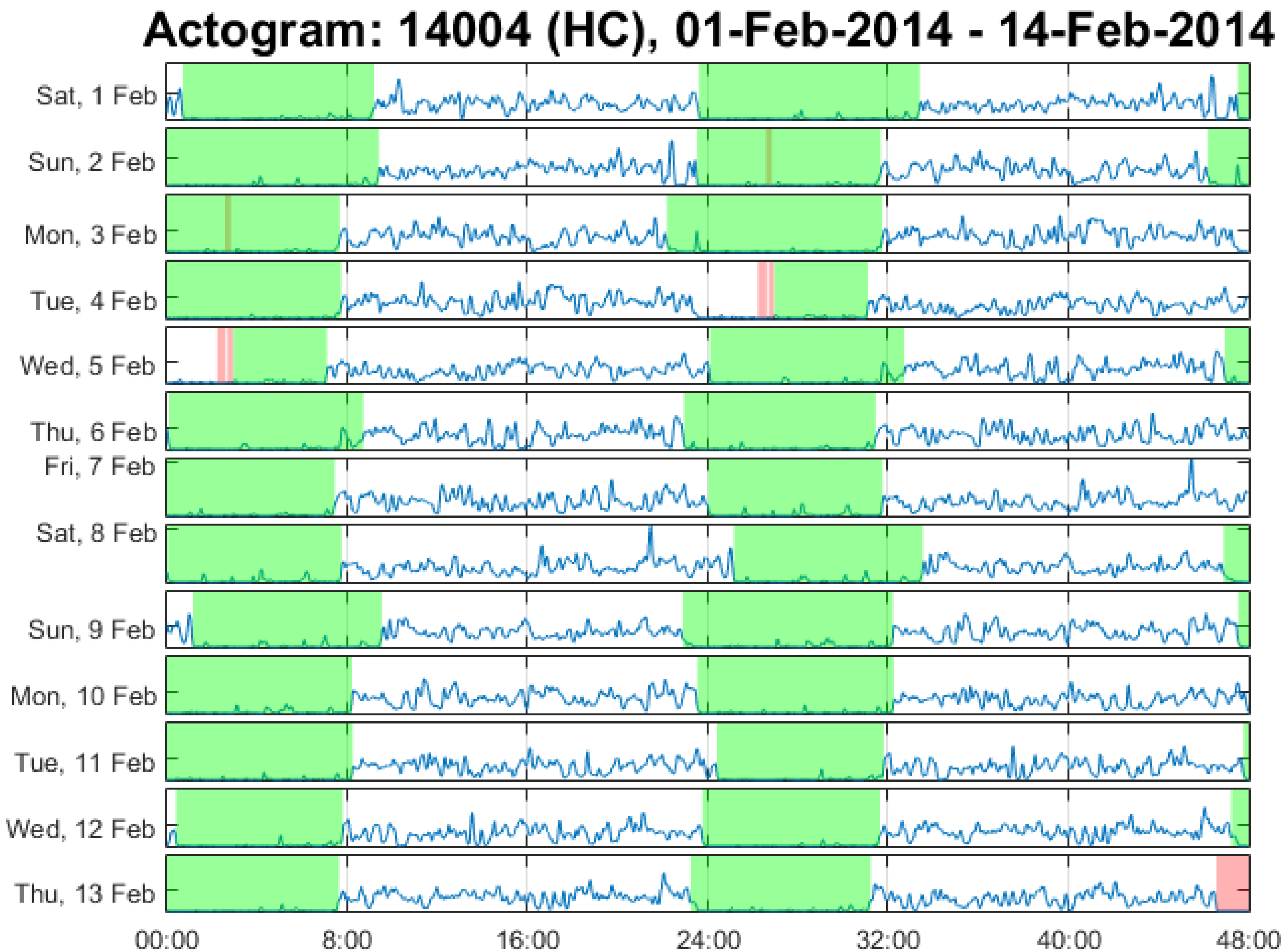
Other

- Sleep diary
- Jawbone

Sleep detection comparisons

	van Hees et al. (2015) sleep detection algorithm		Proposed sleep detection algorithm in this study	
	Sleep onset	Sleep offset	Sleep onset	Sleep offset
Non-traumatised controls	-56±112	22.5±106	-12.5±51	2±30.25
Traumatised controls	-81±147	35.5±95.5	-18±50	10±46.75
PTSD participants	-78±131.25	41.5±122.5	-34±78.25	10±45.25

Objective signal monitoring



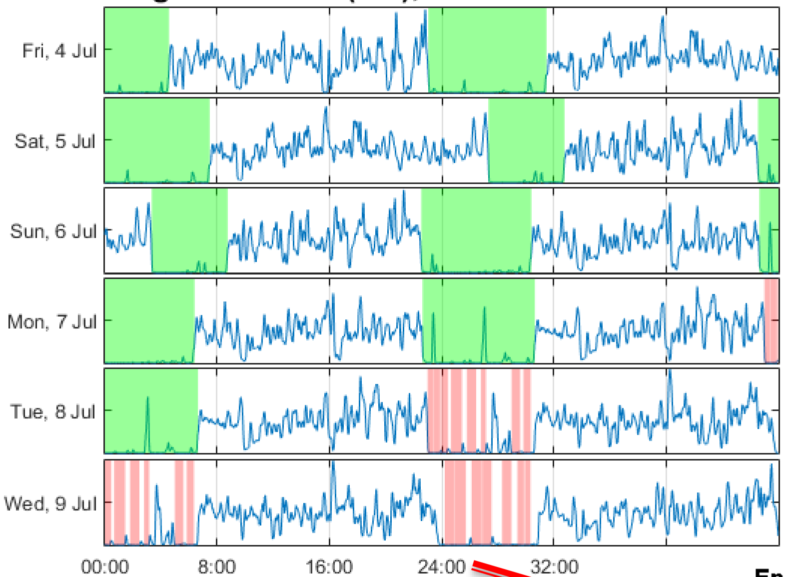
Feature	Subject id
IS	0.66 ± 0.07
IV	0.01 ± 0.00
L5	0.00 ± 0.00
M10	0.16 ± 0.01
RA	0.95 ± 0.02

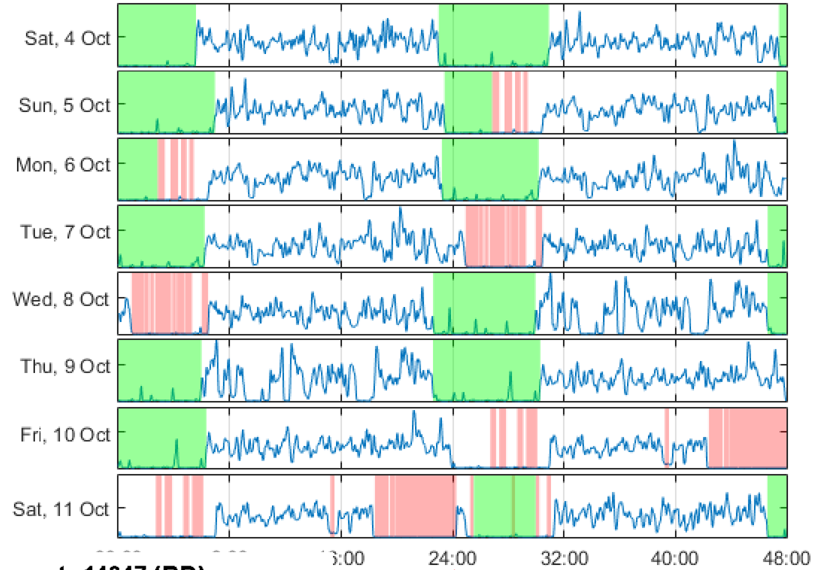
(results in form: median±iqr)

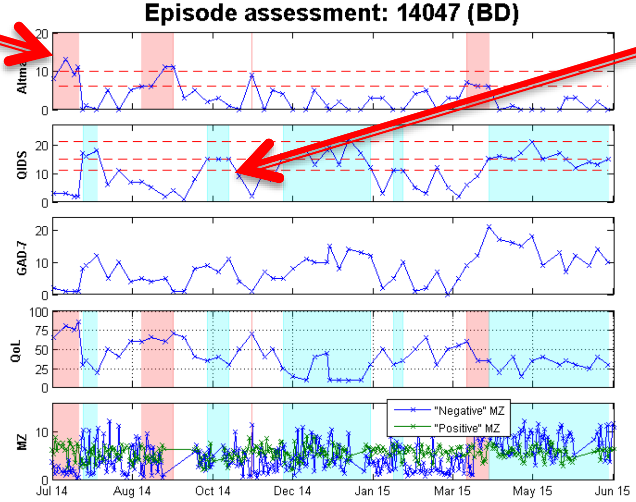
IS = interdaily stability
IV = intradaily variability
RA = relative amplitude = (M10-L5)/(M10+L5)

High IS: good zeitgeber sync ☺
High IV: fragmentation ☹
High RA: good rhythmicity ☺

Smartwatch processing





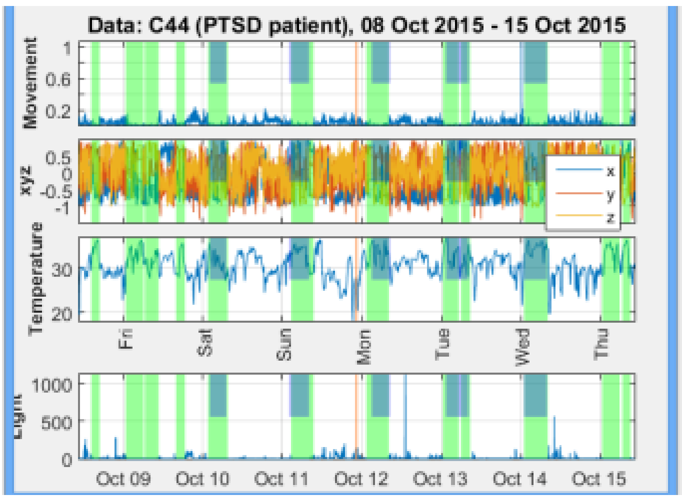


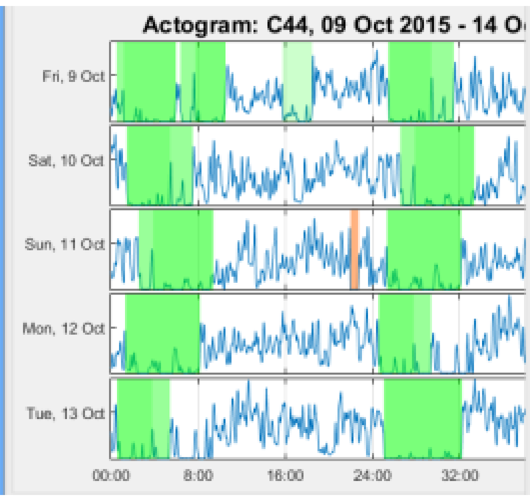
Feature	14047
IS	0.65 ± 0.09
IV	0.01 ± 0.00
L5	0.00 ± 0.00
M10	0.17 ± 0.00
RA	0.95 ± 0.04

Feature	14047
IS	0.72 ± 0.08
IV	0.01 ± 0.00
L5	0.00 ± 0.00
M10	0.17 ± 0.02
RA	0.97 ± 0.03

PTSD, before and after treatment

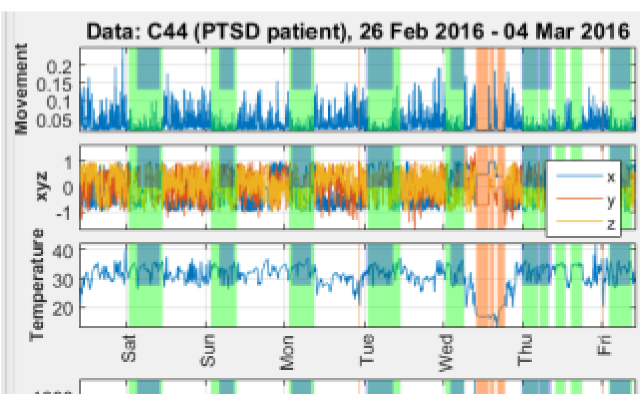
BEFORE CBT

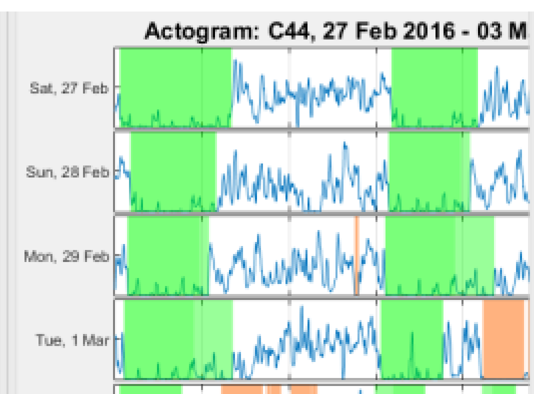




	09 Oct	10 Oct	11 Oct	12 Oct
M10	0.15	0.16	0.14	0.15
L5	0.01	0.01	0.01	0.02
RA	0.86	0.86	0.89	0.80
IS	0.62	0.59	0.58	0.65
IV	0.02	0.02	0.02	0.02
mean activity	5.54	10.01	8.27	9.75
sleep onset	01:27	02:32	01:19	00:33
sleep offset	07:28	09:21	08:08	05:22
sleep duration	06:01	06:49	06:49	04:48
sleep onset phase	57.00	65.00	-73.00	-46.00
sleep offset phase	93.00	113.00	-73.00	-166.00
sleep_activity 1%	0.73	0.97	0.97	1.10
sleep_activity 5%	1.57	1.57	1.31	1.31
sleep_activity 10%	2.27	2.01	1.58	1.44
sleep_entropy	3.01	3.19	2.92	3.05
sleep temp zenith	35.50	35.42	36.34	36.70
sleep temp zenith time	01:55	03:49	07:17	01:42

AFTER CBT





	27 Feb	28 Feb	29 Feb	01 Mar
M10	0.17	0.13	0.15	0.19
L5	0.01	0.00	0.01	0.01
RA	0.92	0.94	0.87	0.91
IS	0.76	0.69	0.61	0.76
IV	0.01	0.01	0.01	0.01
mean activity	9.42	6.51	8.36	7.95
sleep onset	01:24	01:08	00:49	00:24
sleep offset	09:18	08:38	10:50	06:09
sleep duration	07:54	07:30	10:00	05:44
sleep onset phase	58.00	-16.00	-19.00	-25.00
sleep offset phase	-86.00	-40.00	132.00	-281.00
sleep_activity 1%	1.50	1.44	0.92	1.75
sleep_activity 5%	1.85	1.87	1.48	2.17
sleep_activity 10%	3.15	2.51	1.74	3.51

Parkinson's disease revisited

Dundee-Edinburgh Parkinson's Initiative

Esther Sammler

Gordon Duncan

LOngitudinal Monitoring of PARkinson's Disease symptom progression: the LOMPARD study

Anne Steinberg

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Usher Institute
Population Health Sciences & Informatics

The University of Edinburgh

University of Dundee · The University of Edinburgh · Usher Institute Population Health Sciences & Informatics · Euan MacDonald Centre for Motor Neurone Disease Research · Anne Rowling Regenerative Neurology Clinic

The LOMPARD study

- Problems: snapshot that is used for clinical decision making, Hawthorne effect, real life, under recognition of NMS

- Aim: create a way to monitor symptoms that is clinically useful for both the patient and the clinical team

- Emphasis on Non-motor symptoms

Study design

- 50 people for 1 year, early- mid stage PD

- Motor Symptoms:
  - Smartwatch and app tasks
- Non motor symptoms:
  - Sleep, Neuropsychiatric, Autonomic
  - At home

- In person assessment:
  - UPDRS, MoCA
  - Pre and post study interview

-	1	2	3	4	5	6	7	8	9	10	11	12	13

Study aims

- Provide an insight into symptom progression in real life settings
- Help clinical decision making
- Help in self management of symptoms
- Better outcome measures for clinical trials

Interested in participating?

We are looking for people with early-mid stage PD.

If you are interested in participating or would like more information email me at anne.steinberg@ed.ac.uk

Our vision for PD telemonitoring

Data sources

Clinical expertise

Patient input

Fuse data

Human input

Improve care

Acknowledgments

Esther Sammler
Gordon Duncan
Dave Breen
Tilo Kunath
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