Wearable Sensing Systems in Parkinson's Disease

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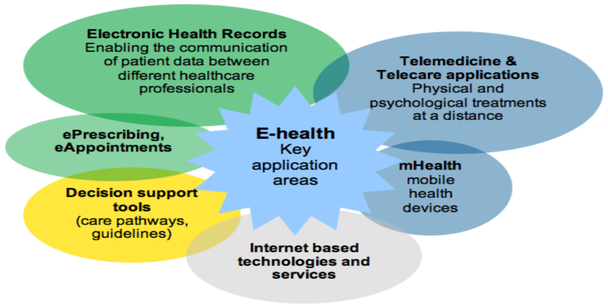
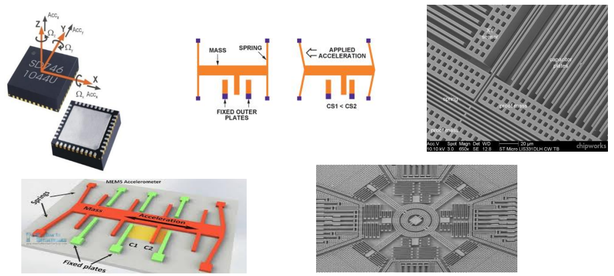
E-Health and Telemedicine

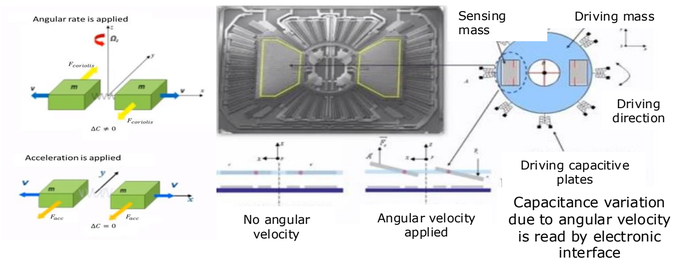



WEARABLE BIOSENSOR
• Examples of wearable biosensor:
Ring Biosensor
Shoes Biosensor
Shirt Biosensor
Nilha

Sensors: Accelerometer



Sensors: Gyroscope

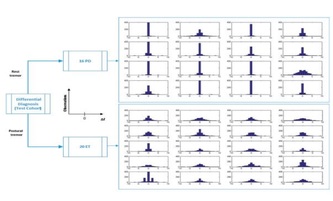


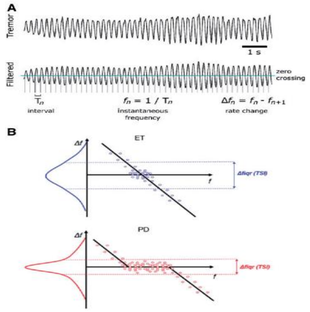
Tremor

doi:10.1093/brain/aww104 BRAIN 2017: 140, 1977–1986 | 1977
BRAIN
A JOURNAL OF NEUROLOGY

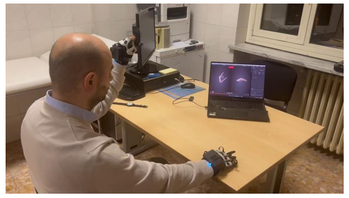
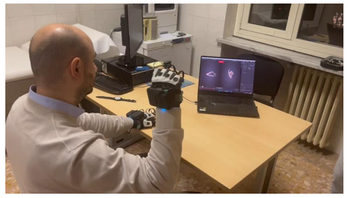
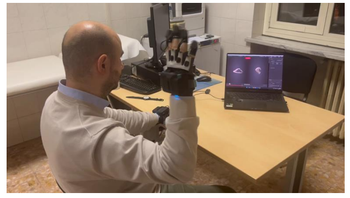
Tremor stability index: a new tool for differential diagnosis in tremor syndromes

Lazzaro di Biase,[1,2,3,*] John-Stuart Brittain,[2,3,*] Syed Ahmar Shah,[2,3] David J. Pedrosa,[2,3,4] Hayriye Cagnan,[2,3] Alexandre Mathy,[2] Chiung Chu Chen,[5] Juan Francisco Martin-Rodriguez,[2,6] Pablo Mir,[6,7] Lars Timmerman,[8,8] Petra Schwingenschuh,[9] Kailash Bhatia,[10] Vincenzo Di Lazzaro[1] and Peter Brown[2,3]

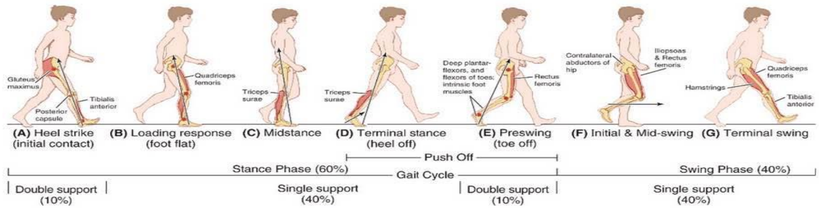


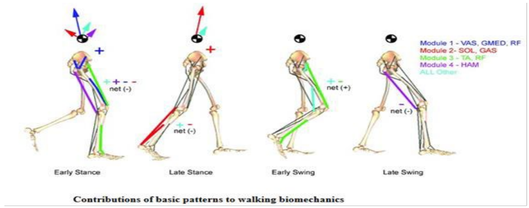


Bradykinesia


Gait





Contributions of basic patterns to walking biomechanics

Sensor Placement



Suppa et al., 2017

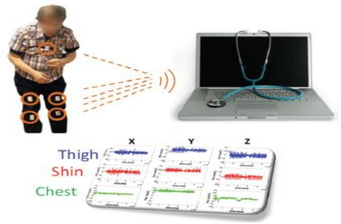


Figure 1: Sketch of the sensing system.

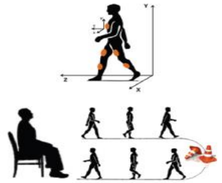
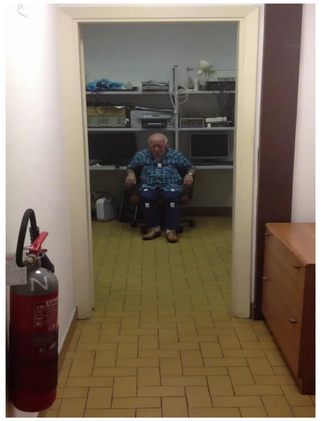


Figure 4: Sketch of the axis orientation and TUG.



Suppa et al., 2017

Suppa et al., 2017

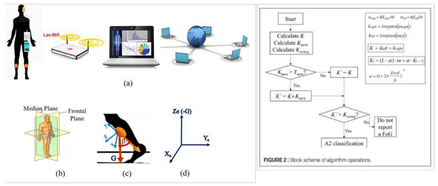


FIGURE 2 | Block scheme of algorithm operations.

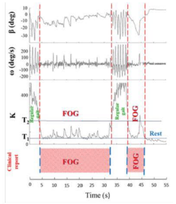


TABLE 2 | Average (±SD) Timed Up and Go (TUG) duration, total freezing of gait (FOG) duration, step velocity, stride length, stride time, and cadence in healthy subjects and Parkinson's disease (PD) patients with and without FOG, OFF and ON therapy.

Subjects	State of therapy	TUG duration (s)	FOG duration (s)	Step velocity (cm/s)	Stride length (cm)	Stride time (s)	Cadence (steps/min)
Healthy subjects		10.6 ± 5.7		118.7 ± 37.17	77.7 ± 32.11	0.8 ± 0.10	111.2 ± 14.25
PD patients with FOG	OFF	69.9 ± 38.18	39.5 ± 63.50	76.0 ± 32.66	45.7 ± 26.49	0.8 ± 0.17	97.3 ± 16.18
	ON	31.4 ± 17.24	22.9 ± 48.37	96.6 ± 28.03	60.3 ± 20.74	0.8 ± 0.13	105.5 ± 22.67
PD patients without FOG	OFF	24.4 ± 7.79		71.4 ± 22.50	52.6 ± 21.25	0.9 ± 0.13	107.0 ± 18.83
	ON	21.5 ± 6.56		74.7 ± 19.61	48.0 ± 21.17	0.8 ± 0.17	106.2 ± 17.62

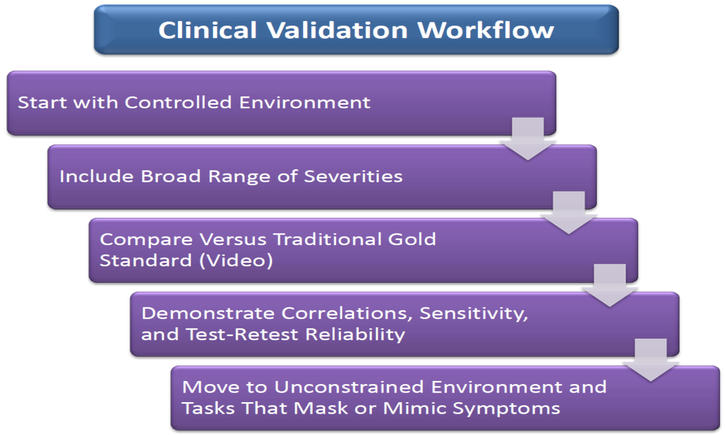
l-DOPA and Freezing of Gait in Parkinson's Disease: Objective Assessment through a Wearable Wireless System

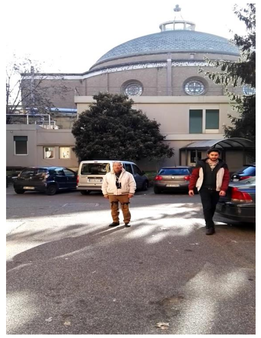
Antonio Suppa · Ardian Kita · Giorgio Leodori · Alessandro Zampogna · Ettore Nicolini · Paolo Lorenzi · Rosario Rao · Fernanda Irrera

Frontiers in Neurology
Published on 14 Aug 2017
OPEN ACCESS

Suppa et al., 2017

Suppa et al., 2017


Clinical Validation Workflow
Start with Controlled Environment
Include Broad Range of Severities
Compare Versus Traditional Gold Standard (Video)
Demonstrate Correlations, Sensitivity, and Test-Retest Reliability
Move to Unconstrained Environment and Tasks That Mask or Mimic Symptoms



Mazzetta et al., 2018, 2019

Article

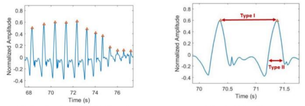
Prediction of Freezing of Gait in Parkinson's Disease using Wearables and Machine Learning

Luigi Borzi [1*], Ivan Mazzetta [2], Alessandro Zampogna [3], Antonio Suppa [3,4], Gabriella Olmo [1], Fernanda Irrera [2]

(a) Sketch of wearable device positioning and inertial reference frame

(b) Exploded view of the neMEMSi device.

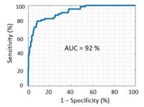
Figure 1. Sensor positioning and composition



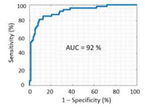
(a) Signal peaks identified by the peak detection algorithm (red triangles)

(b) Type I and Type II segments.

Figure 3. Peak detection and signal segmentation.



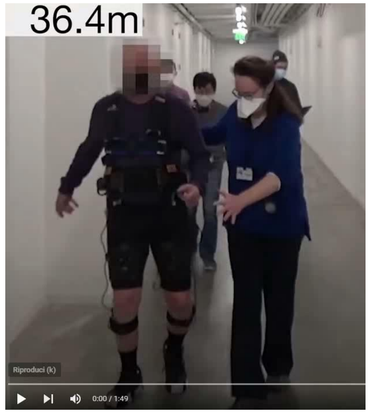
(a) ON therapy



(b) OFF therapy

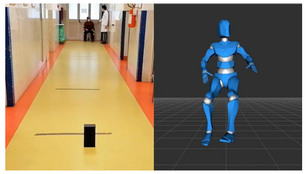
Figure 7. ROC curves of the final classification model, for patients ON and OFF therapy.

Borzi et al., 2021


36.4m
Riproduci (k)
0:00 / 1:49


27.1m
[ASSIST ON]

UPDRS and Sensors



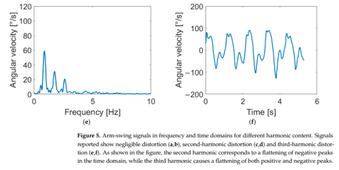
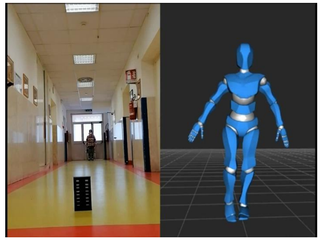
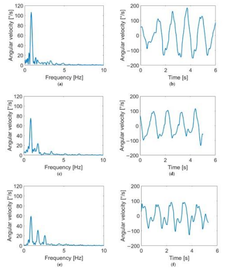


Figure 5. Arm-swing signals in frequency and time domains for different harmonic content. Signals reported show negligible distortion (**a**,**b**), second-harmonic distortion (**c**,**d**) and third-harmonic distortion (**e**,**f**). As shown in the figure, the second harmonic corresponds to a flattening of negative peaks in the time domain, while the third harmonic causes a flattening of both positive and negative peaks.

Pietrosanti et al., 2023

ARM SWING REDUCTION IN PD

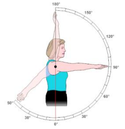




Pietrosanti et al., 2023

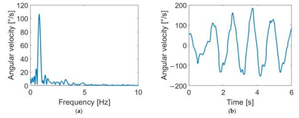
Analisi nel dominio del tempo

- Range of Motion di spalla e gomito (**S-ROM** e **E-ROM**)
- Velocità di oscillazione della spalla e del gomito (**S-velocity** e **E-velocity**);
- Indice di asimmetria della spalla e del gomito (**Asym-S** e **Asym-E**)



Analisi nel dominio della frequenza

- Ampiezza delle armoniche fondamentali del braccio superiore e dell'avambraccio (**HA1** e **HF1**)
- Indice di asimmetria delle armoniche fondamentali (**Asym-HA1** e **Asym-HF1**)



Correlazioni Clinico-comportamentali

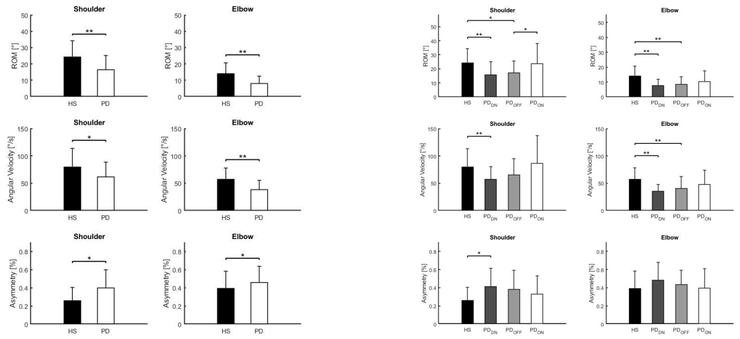
- **Correlazioni** tra subitems MDS-UPRS III (per rigidità e bradicinesia) e parametri cinematici

UPDRS-III items	Before taking zolpidem	After taking zolpidem
Speech	3	2
Facial expression	3	2
Resting tremor	7	7
Action or postural tremor on hands	4	4
Rigidity	11	6
Finger taps	5	3
Hand movement	5	3
Rapid alternative movement of hands	5	3
Leg agility	5	3
Arising from chair	3	2
Posture	3	3
Gait	3	2
Postural instability	2	2
Slow movement	3	2
Total score	62	44
Improvement (%)		29%

UPDRS, unified Parkinson disease rating scale.

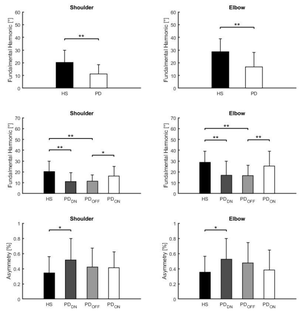
Patera et al. Under Review

Analisi nel dominio del tempo

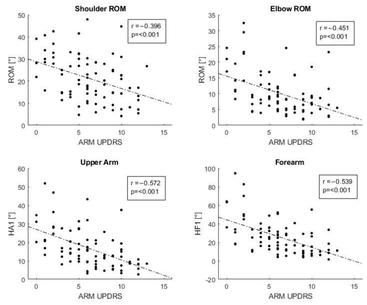


Patera et al. Under Review

Analisi nel dominio della frequenza

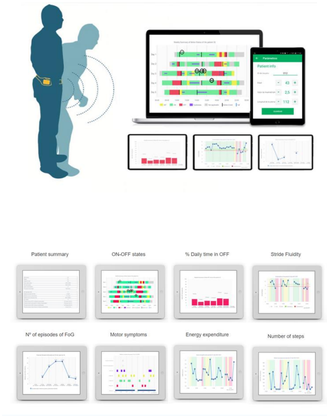


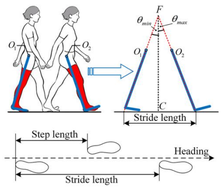
Correlazioni clinico-comportamentali

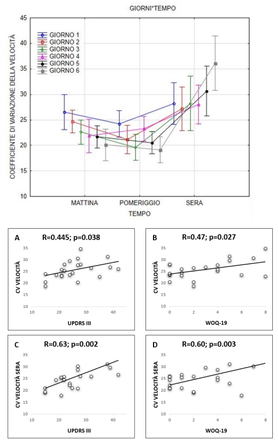


Patera et al. Under Review

Telemetry in PD

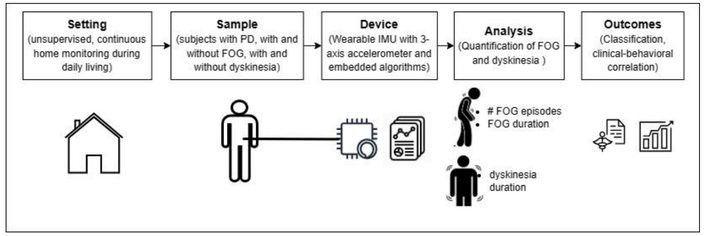






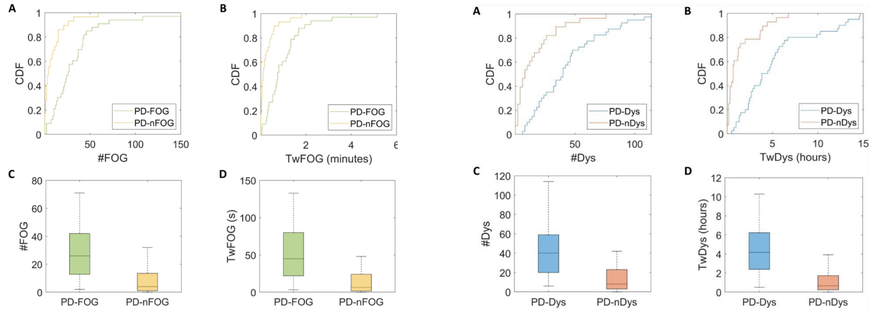
Suppa et al., Unpublished data

Telemetry in PD



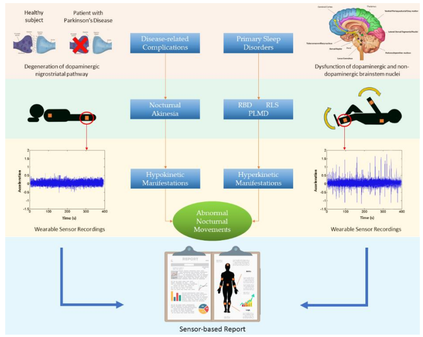
Zampogna et al., 2024

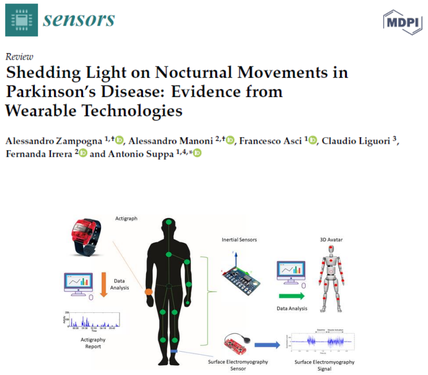
Telemetry in PD



Zampogna et al., 2024

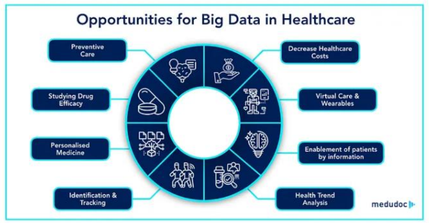
Abnormal Nocturnal Movements in PD





Zampogna et al., 2020

E-Health, Telemedicine, Domotic and Internet of Things



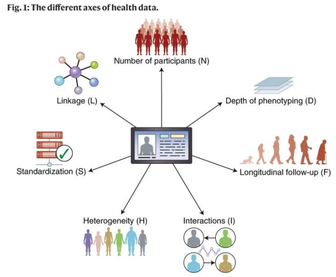


Fig. 1: The different axes of health data.

The complexity of large health datasets can be represented by distinct axes, each encompassing a quantifiable property of the data.

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***S**apienza Information-Based **T**echnology Innova**T**ion **C**enter for **H**ealth*

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