Prédiction du risque de chute via l'estimation des caractéristiques de la marche à l'aide de capteurs embarqués

Naima Al Abiad, Thomas Robert et Valerie Renaudin

Funded by: The Mobility and Digital Transition project

MOBILITE' TRANSITION NUMERIQUE

UNIVERSITÉ DE LYON

Université Gustave Eiffel

Contents

- Introduction
- Controlled environment test
- Measurements in Elderly and young
- Machine learning and improved step detection
- Conclusion and Future work

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Introduction

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Falls

Common

1/4 of people over 65 fall at least once a year

(Alexander, Rivara, & Wolf, 1992)

Costly

Cost of fall related care

30,000,000,000 $

(Burns, Stevens, & Lee, 2016)

Harmful

1in5 falls in older adults results in major injuries

(Sterling, O'Connor, & Bonadies, 2001)

Each year at least 300,000 older people hip fractures

(Boslaugh, 2016)

6th VITAL SIGN

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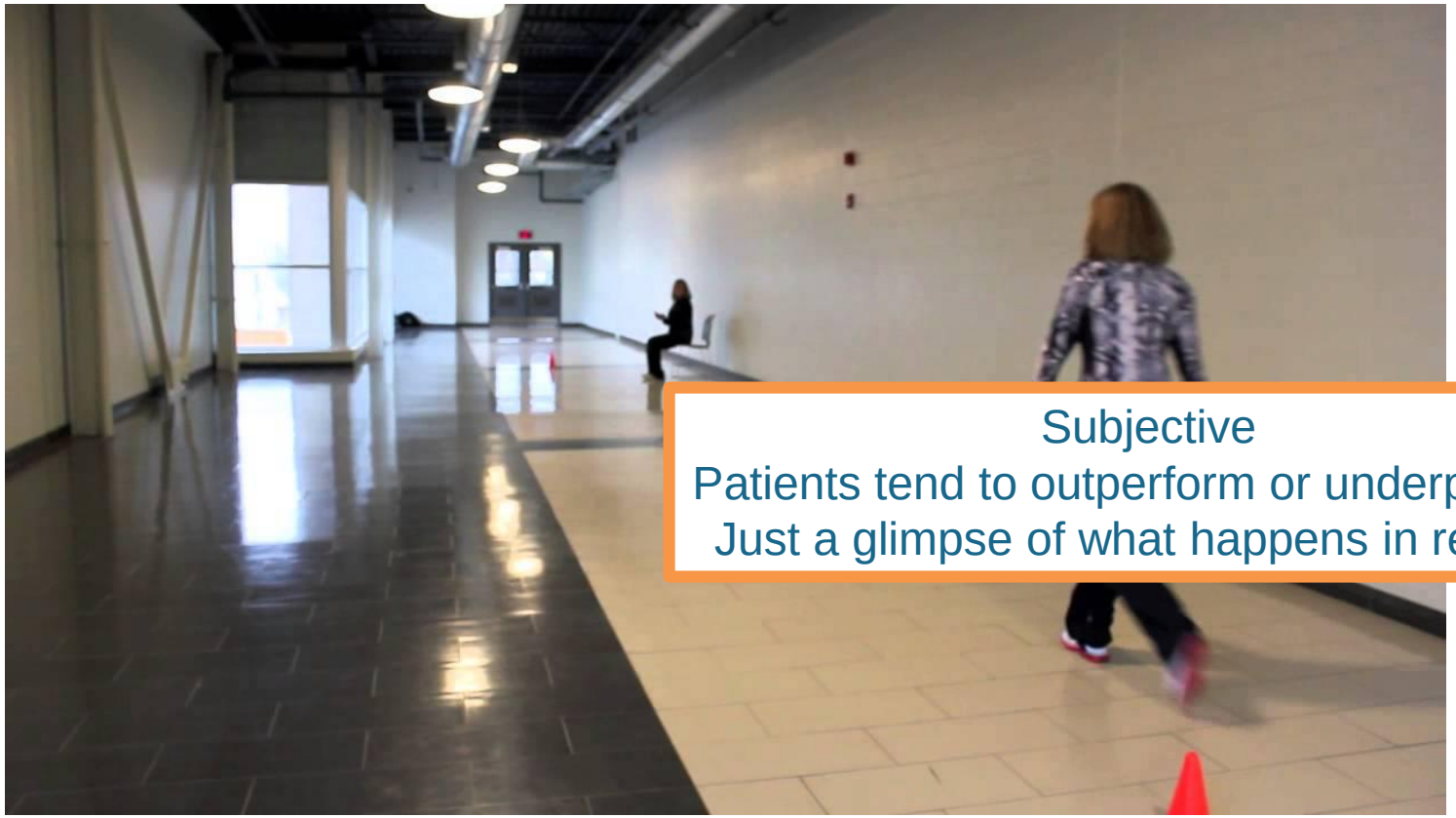
Visual assessments



Subjective
Patients tend to outperform or underperform
Just a glimpse of what happens in real life

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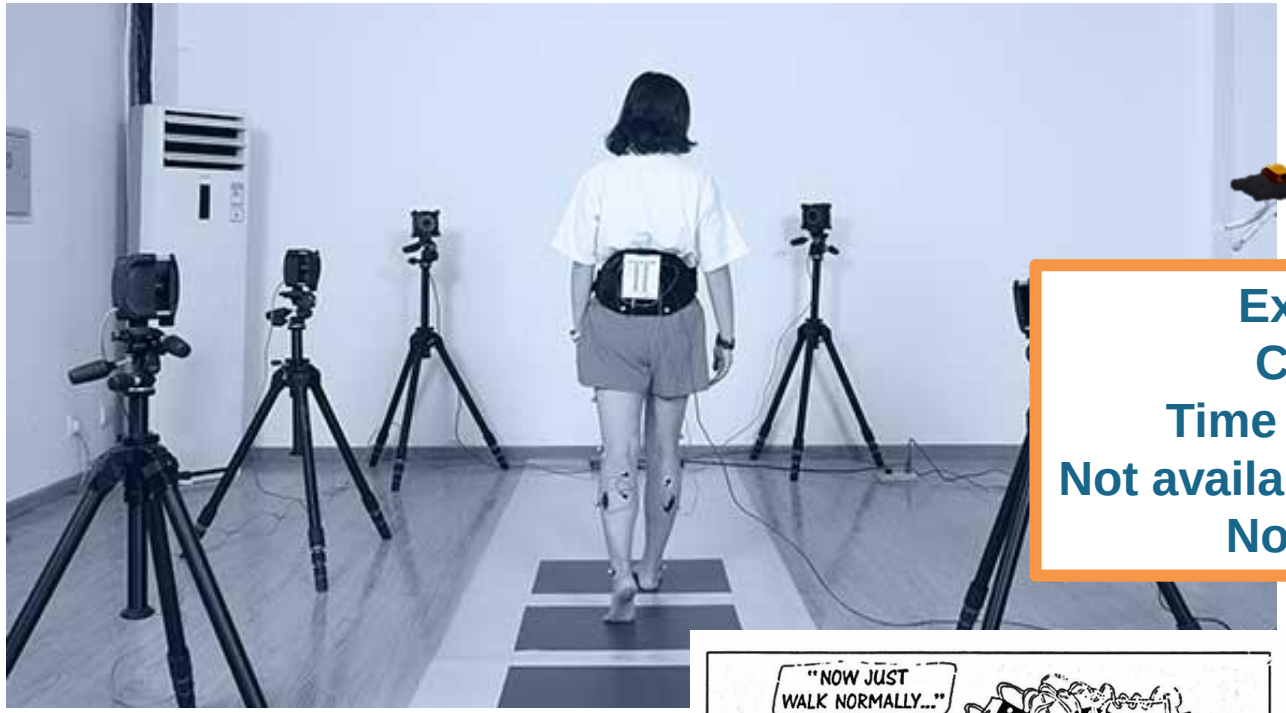
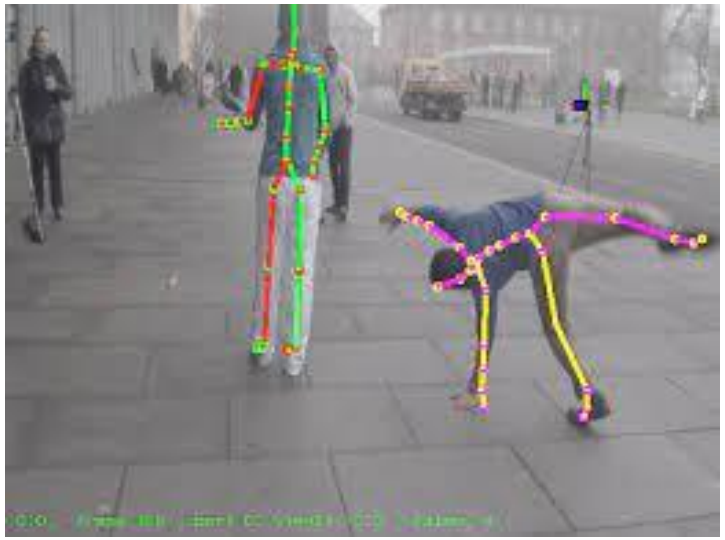
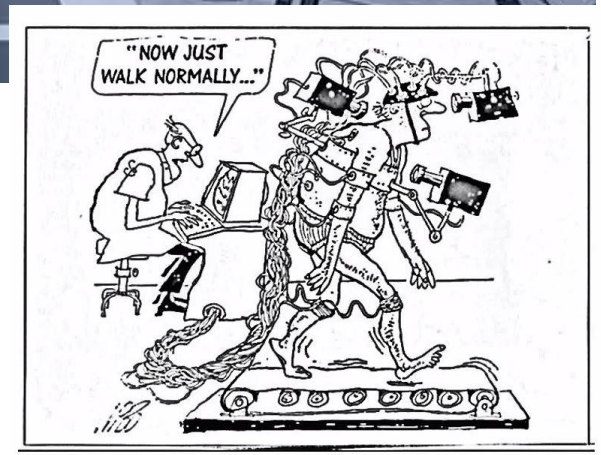
Laboratory assessments



Expensive
Complex
Time consuming
Not available for everyone
Not real life





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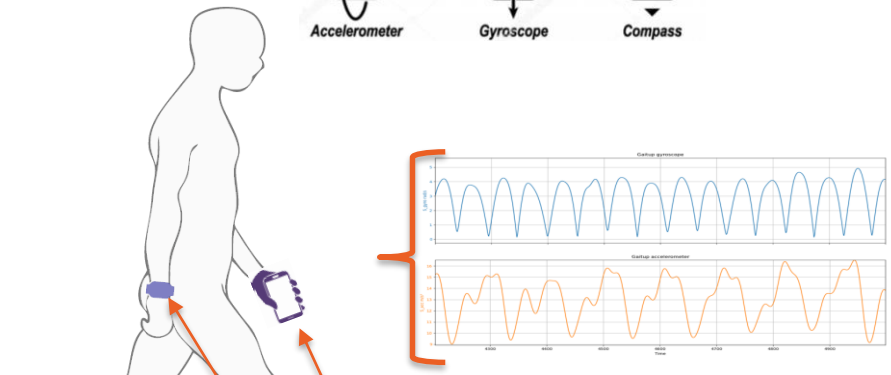
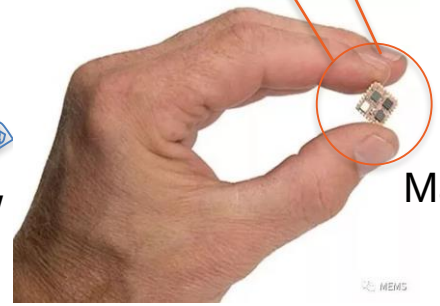
Accelerometers discovered 1975

Size reduced
Cost reduced

Now





Acceleration
Angular velocity
Magnetic field

Inertial measurement units

Use IMU found in everyday embedded devices to assess gait

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Review

Smartphone-Based Solutions for Fall Detection and Prevention: Challenges and Open Issues

Mohammad Ashfak Habib [1,2,3], Mas S. Mohktar [1,2], Shahrul Bahyah Kamaruzzaman [2,4], Kheng Seang Lim [2,4], Tan Maw Pin [2,4] and Fatimah Ibrahim [1,2,*]

Article

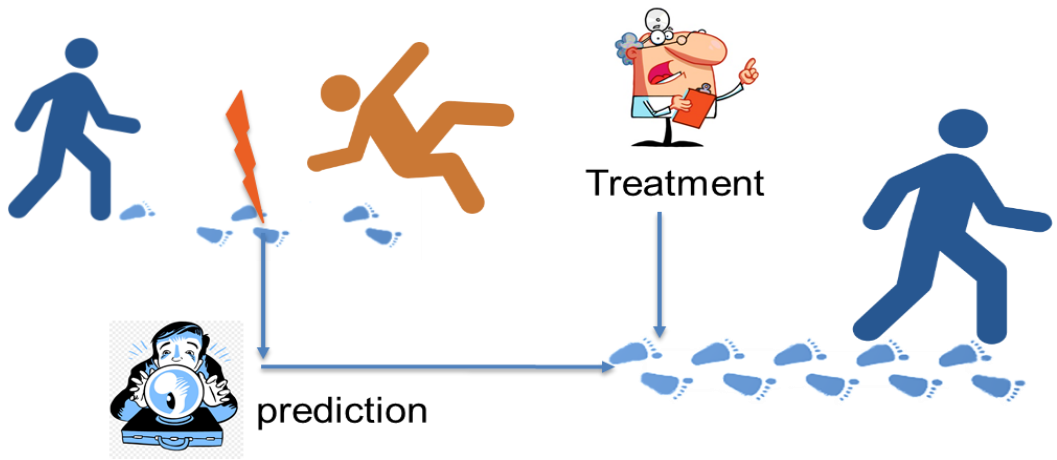
Analysis of Android Device-Based Solutions for Fall Detection

Eduardo Casilari *, Rafael Luque and María-José Morón

Departamento de Tecnología Electrónica, ETSI Telecomunicación, Universidad de Málaga, 29071 Málaga, Spain; E-Mails: rluque@uma.es (R.L.); mjmoron@uma.es (M.-J.M.)

In 2017, **59%** of adults **65–69 years** old, **49%** of adults **70–74 years** old, and **31%** of adults **75–79 years** old are smartphone owners

Go beyond counting steps: Mobility Measures



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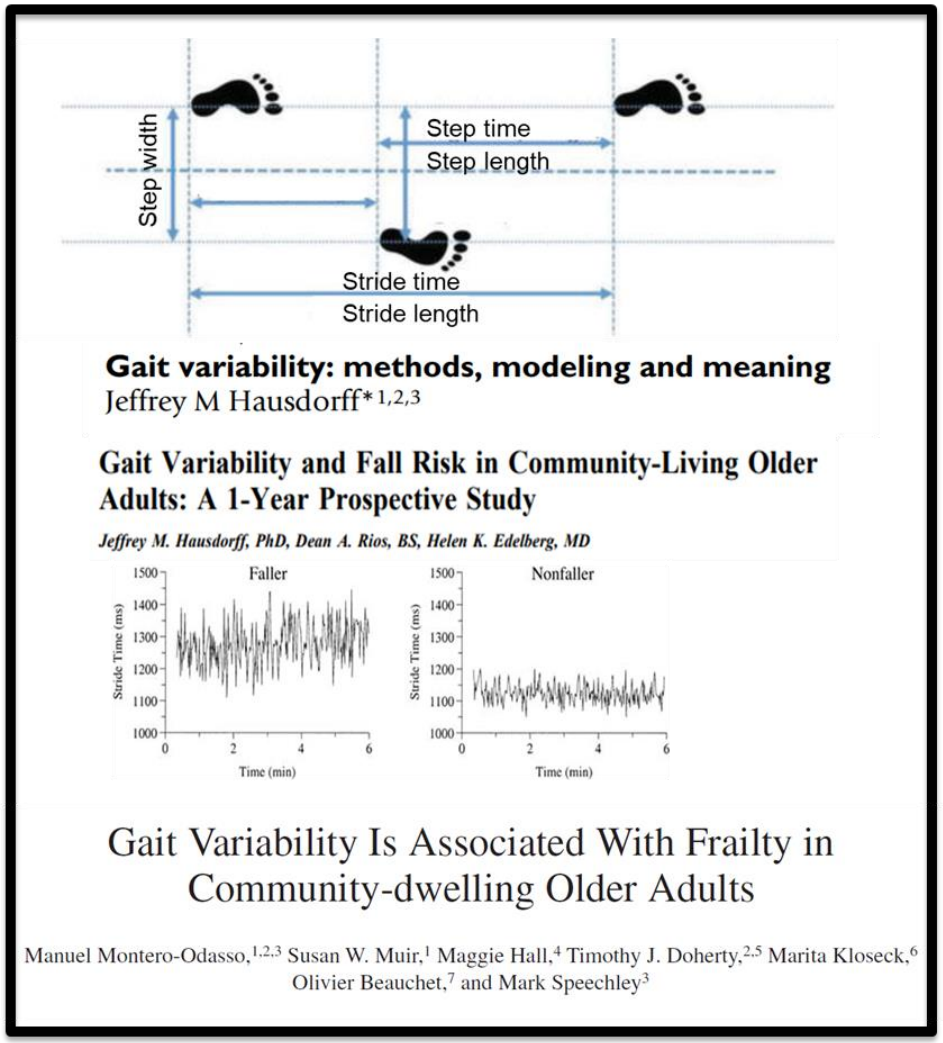
- Gait Variability: Stride time variability

Neuromotor noise is increased, which in its turn results in a greater variability



Gait variability: methods, modeling and meaning
Jeffrey M Hausdorff*[1,2,3]

Gait Variability and Fall Risk in Community-Living Older Adults: A 1-Year Prospective Study

Jeffrey M. Hausdorff, PhD, Dean A. Rios, BS, Helen K. Edelberg, MD

Gait Variability Is Associated With Frailty in Community-dwelling Older Adults

Manuel Montero-Odasso,[1,2,3] Susan W. Muir,[1] Maggie Hall,[4] Timothy J. Doherty,[2,5] Marita Kloseck,[6] Olivier Beauchet,[7] and Mark Speechley[3]

- Non-linear measures: Lyapunov Exponent.

Reflects the ability to recover from small perturbation

Local dynamic stability and variability of gait are associated with fall history in elderly subjects

Marcel J.P. Toebes [a], Marco J.M. Hoozemans [a], Regula Furrer [a], Joost Dekker [b], Jaap H. van Dieën [a,*]

[a] MOVE Research Institute Amsterdam, Faculty of Human Movement Sciences, VU University Amsterdam, The Netherlands
[b] VU University Medical Center, Department of Rehabilitation Medicine, EMGO Institute for Health and Care Research, The Netherlands

RESEARCH ARTICLE

Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study

Lucia Bizovska[1☯]*, Zdenek Svoboda[1☯], Miroslav Janura[1☯], Maria Cristina Bisi[2‡], Nicolas Vuillerme[3,4‡]

Differentiating fall-prone and healthy adults using local dynamic stability

Thurmon E. Lockhart* and **Jian Liu**
Locomotion Research Laboratory, Grado Department of Industrial and Systems Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA

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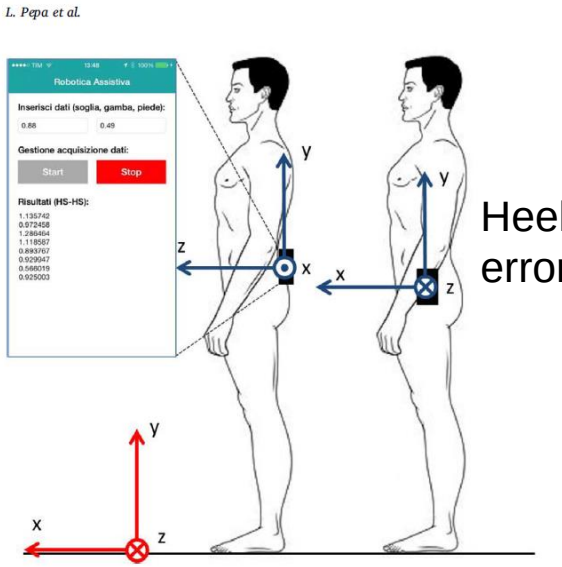
Smartphone sensor Quality?

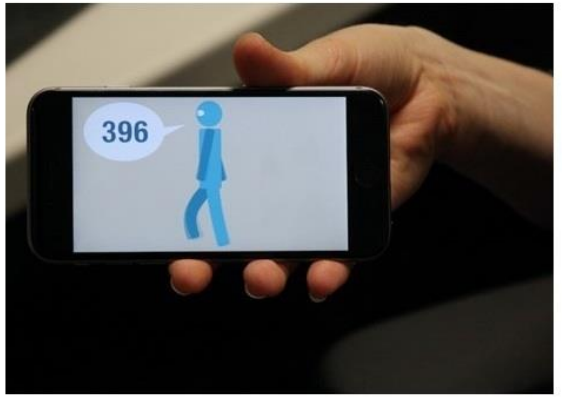


Pepa et al. 2017

Heel Strike detection error of around **7 ms**

Manor et al. 2018

Stride times derived from the smartphone app and a reference device were highly correlated with an error of around **17ms**



Sensor Quality is not the issue

Find a method to process the data and be robust aganist real life activities

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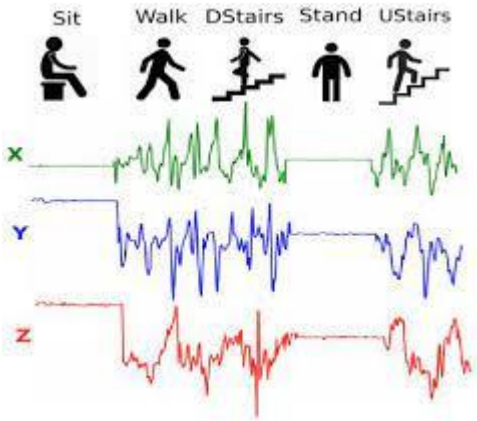
What is real life?

Holding your smartphone the **way you like to hold it**, **doing whatever you like**, **wherever you like**.

It is complex!

Different user behavior

Different walking environments



Different activities

Controlled environment test

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Objective

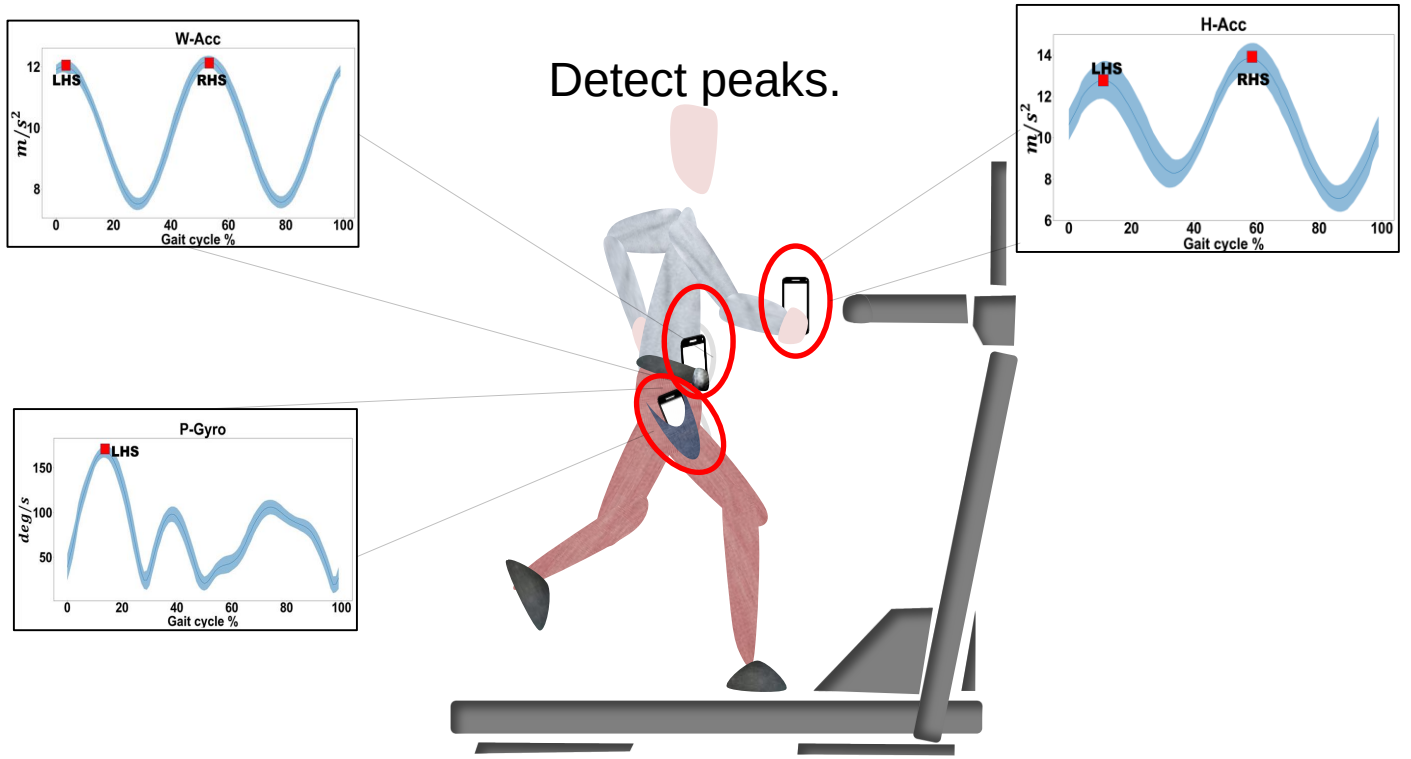
Find a robust way to process the **smartphone Accelerometer and Gyroscope signal** for frequent phone positions to **detect steps** and **calculate stride time variability**

Iphone 6s

Found on the Appstore

Sampling frequency: 100Hz

10 participants average Age~28 years



3 speeds: Comfortable- Low- High and asymmetrical mode

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Preliminary Findings

2 modes

Stable with respect to center of mass

waist

Hand?

Peaks in acceleration

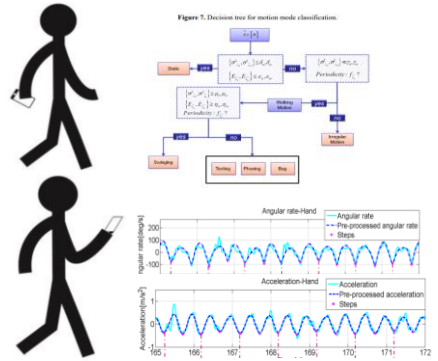
oscillating with respect to center of mass

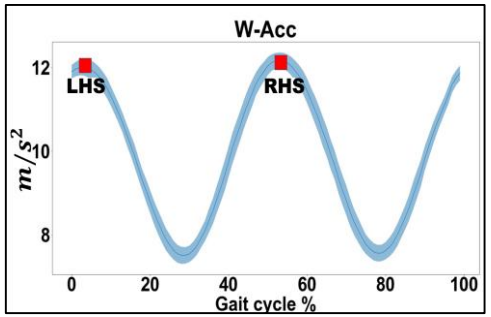
Pocket

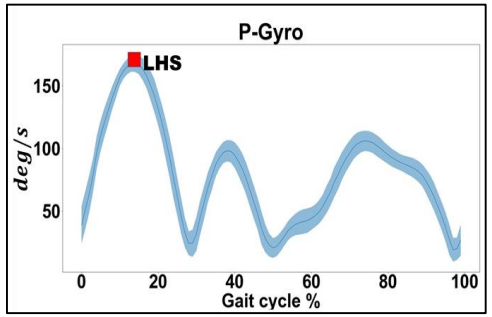
Hand?

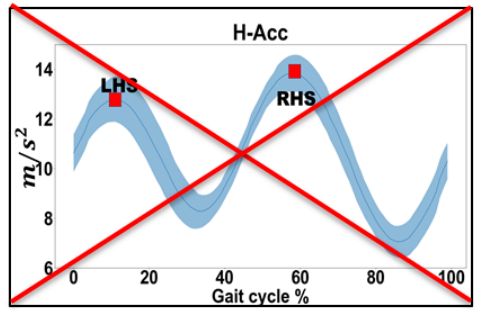
Peaks in angular velocity

Susi et al. 2013









Hand is a more complex: **Motion mode** of the hand affects the signal
Strength of swing affects the signal

To treat mis-detected steps we apply statistical filtering

Remove abnormal strides more than 1,5sec and less than 0,8sec
Remove strides more than 3 SD away from the mean

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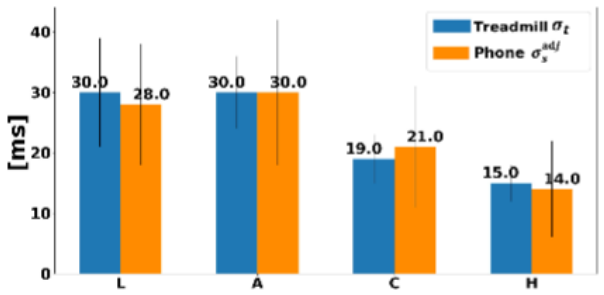
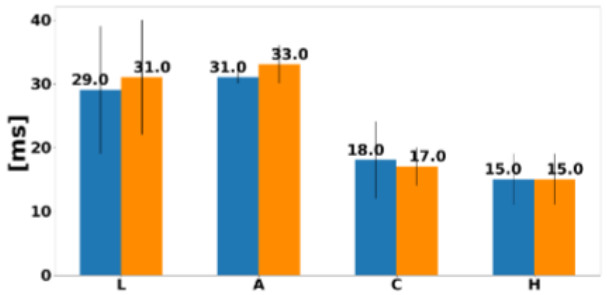
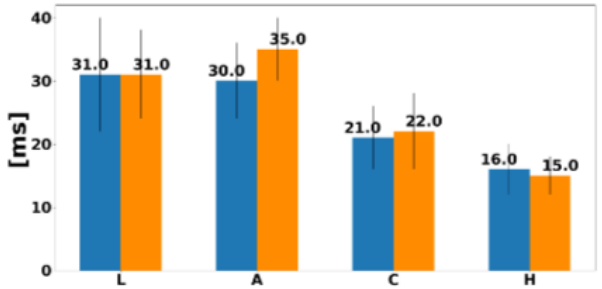
Findings



(a) Hand



(b) Pocket

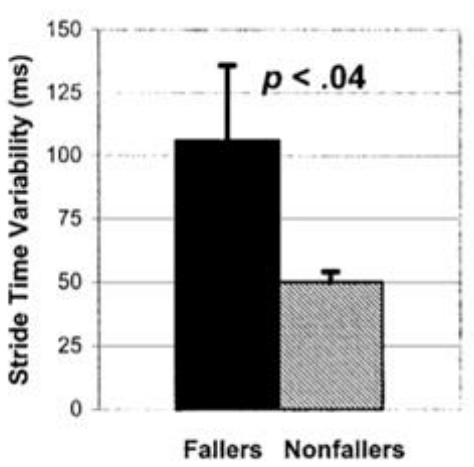


(c) Waist

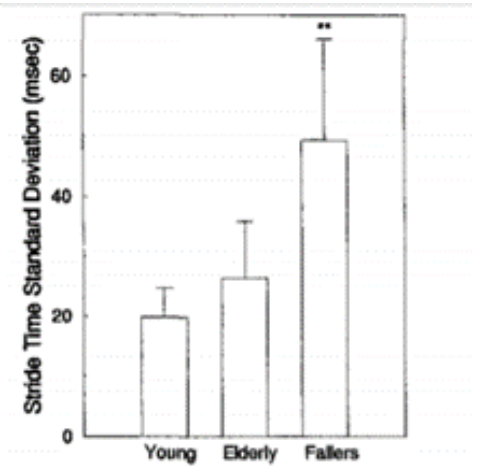
		Treadmill operational mode				
	Placements	slow	comfortable	high		Asymmetrical
Mean σ_t [ms]	waist	31	21	16	†*	30
	pocket	29	18	15	†*	31
	hand	30	19	15	†*	30
Mean σ_s^{adj} [ms]	waist	31	22	15	†*‡	35
	pocket	31	17	15	†*	33
	hand	28	21	14	†	30
RMSE σ_s^{adj} [ms]	waist	6	3	2		4
	pocket	2	3	5		4
	hand	5	9	10		7

* Significance between low and comfortable speed; ‡ Significance between comfortable and high speed; † Significance between low and high speed; No statistical test was done on asymmetrical gait because of the low number of participants.

	Treadmill operational mode			
$\%_{filtered}$	Low	Comfortable	High	Asymmetrical
Waist	1 ± 1	2 ± 4	1 ± 1	$1 \pm 0.$
Pocket	$1 \pm 0.$	2 ± 2	1 ± 2	$0. \pm 0.$
Hand	25 ± 14	14 ± 8	10 ± 6	31 ± 16



(Hausdorff et al., 2001)



(Hausdorff et al., 1997)

Detection of steps is really important:
Must improve

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Measurements in Elderly and Young

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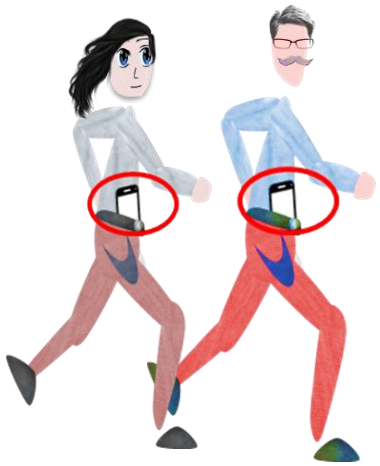
Objective

Calculate **gait variability** and **nonlinear measure**: Lyapunov exponent on elderly and young adults

Enguerren Houdry

ANDROID APP DEVELOPMENT

We developed an android app for hospital physiotherapist to measure phone IMU signals

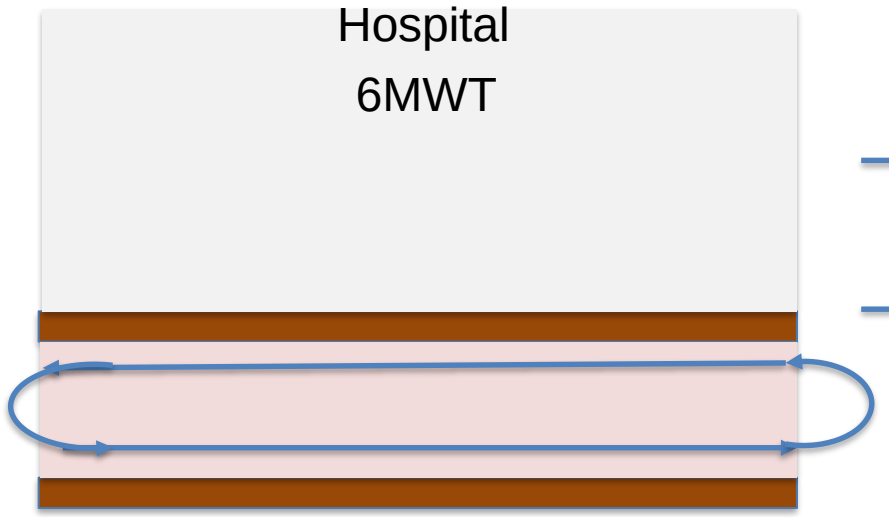


6 young

Expect 10 young

6 old non-fallers

Expect 30 elderly with fallers



Estimate Lyapunov exponent

Estimate Standard deviation of stride time

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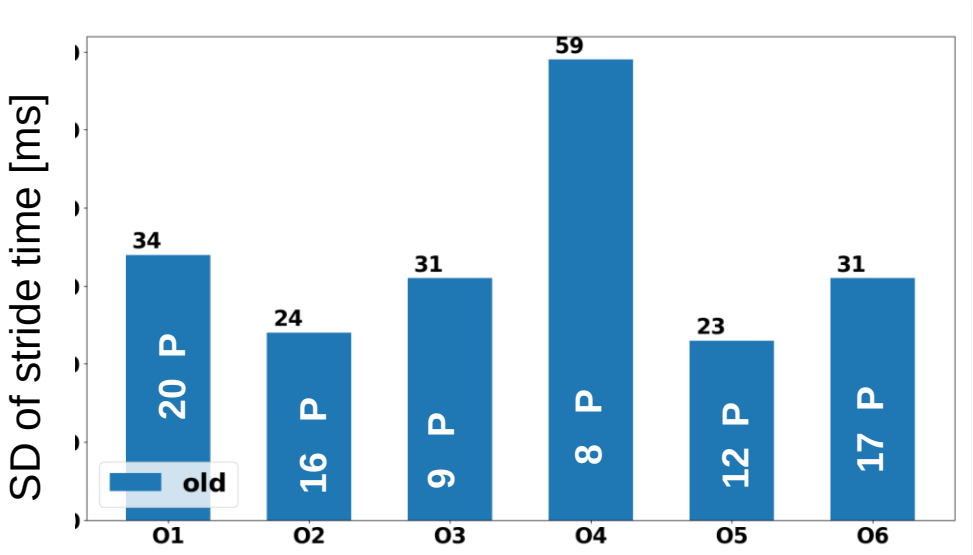
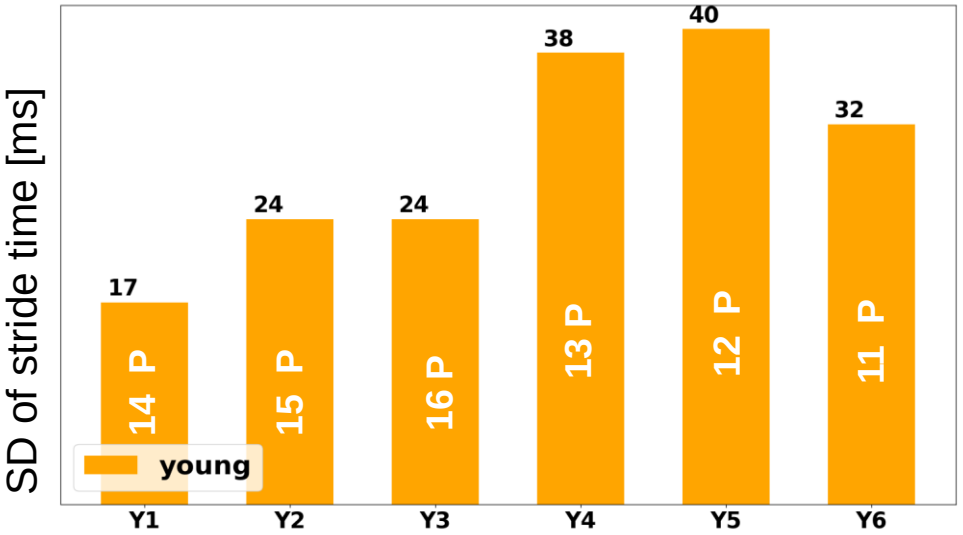
Findings: Gait variability

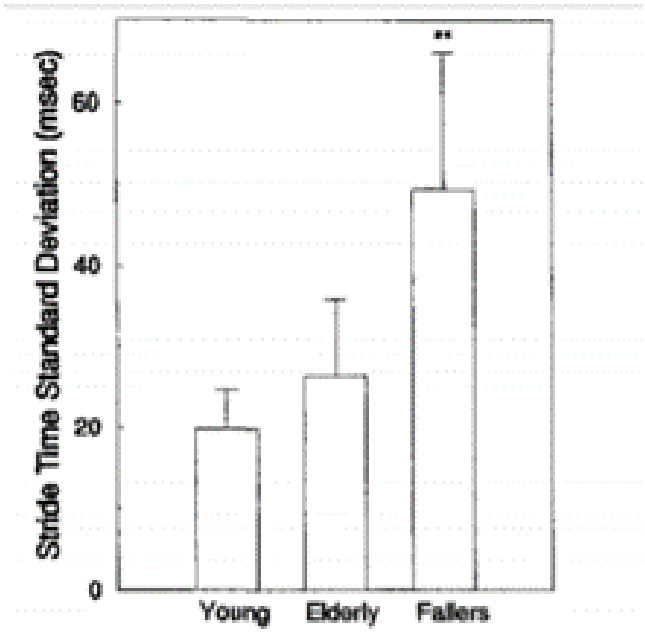


P: pass in hallway



Average: 34 ± 13 ms

Average: 29 ± 8ms



(Hausdorff et al., 1997)

Findings: Lyapunov

What is the Lyapunov exponent?

- Estimates a system's local dynamic stability.
- Reflects the ability to recover from small perturbation
- The higher it is, the worse the system's resistance to local perturbations

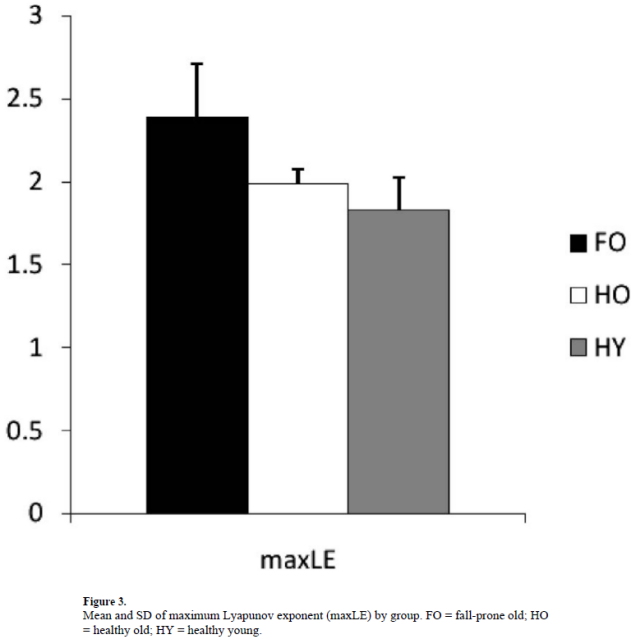
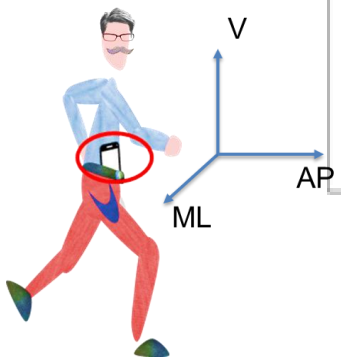
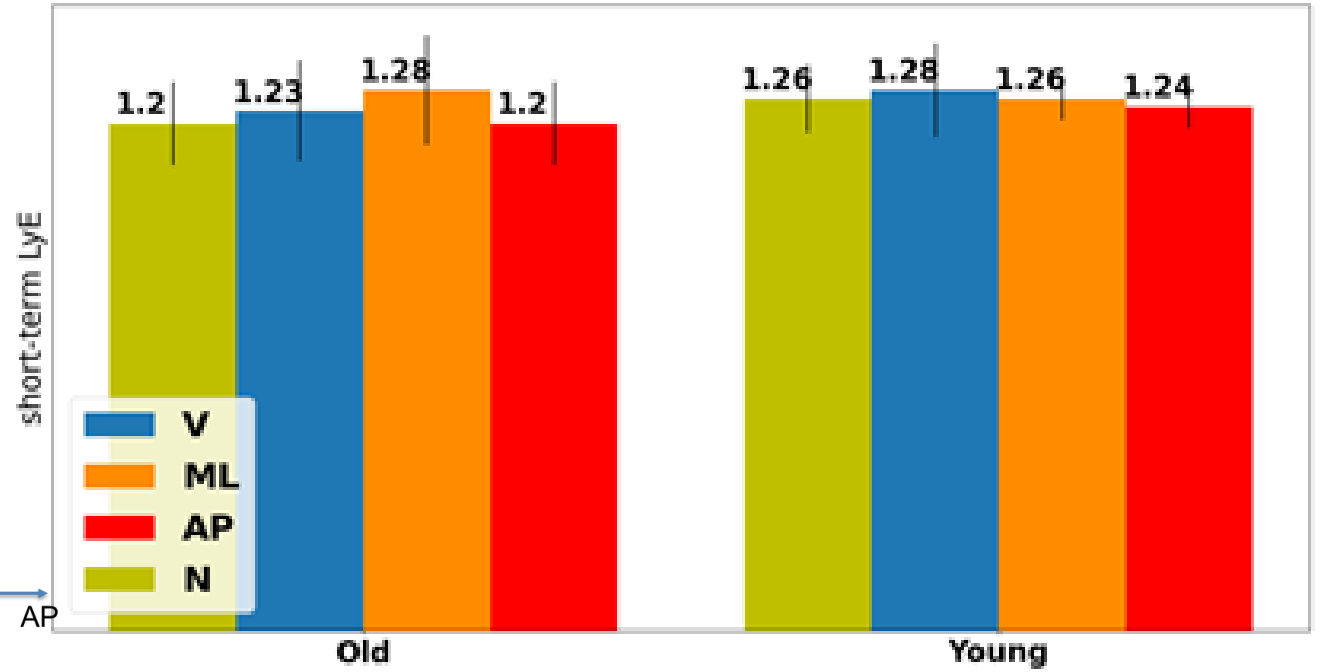


Figure 3.
Mean and SD of maximum Lyapunov exponent (maxLE) by group. FO = fall-prone old; HO = healthy old; HY = healthy young.

Lockhart T. E. and Liu J. (2008)





Machine learning and improved hand step detection

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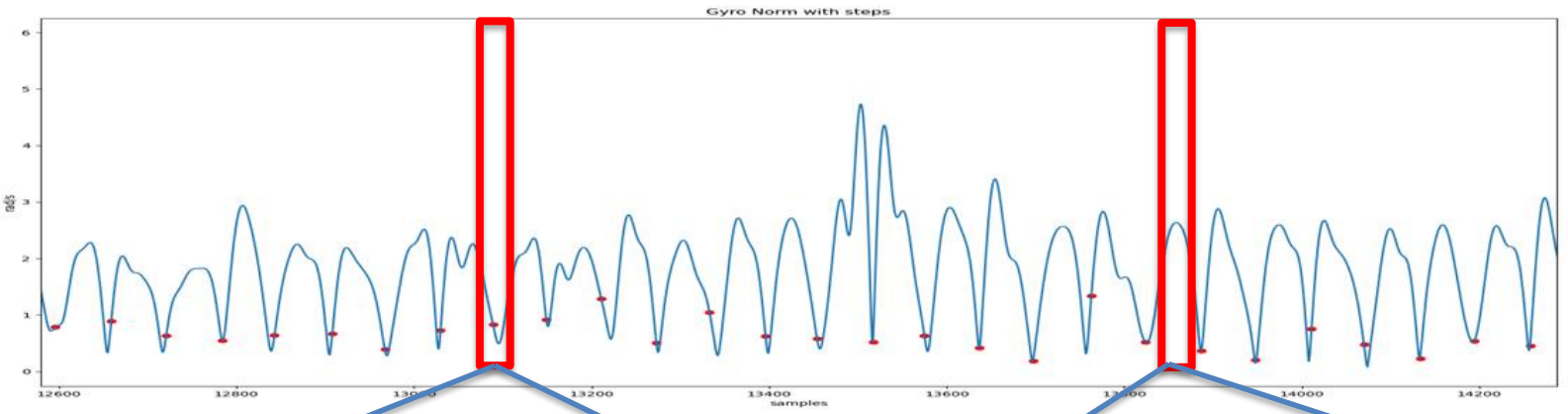
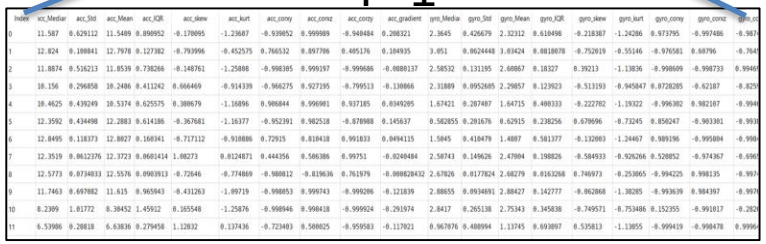
8 subjects walking on treadmill **3 different speeds** for 210 secs and recording **360 steps per speed per subject.**

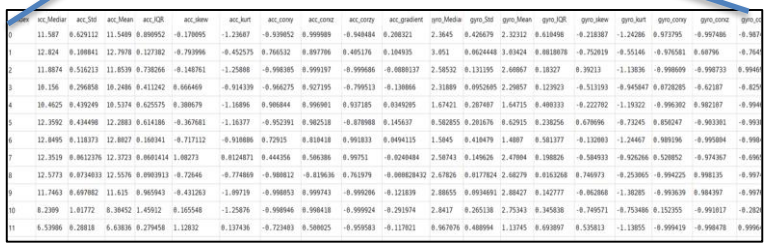
Total number of steps in database: **3*360*8= 8640 examples**



Y=1



Y=0

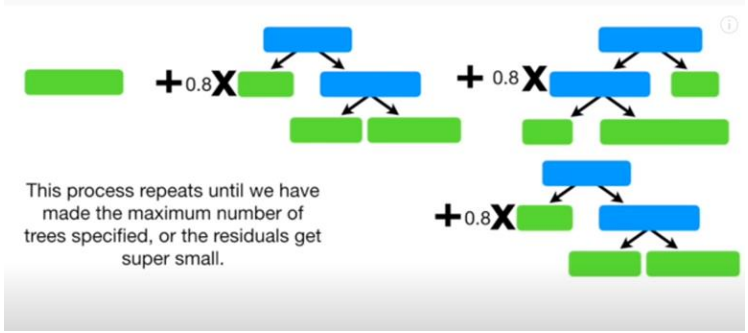


Find a way to associate X and Y using a model

X=Features

Y= 0 if no-step 1 if step occurred

Histogram based Gradient boosting



Sensitivity: 98%

Specificity: 96%

IPIN 2021
ELEVENTH INTERNATIONAL CONFERENCE ON
INDOOR POSITIONING
AND INDOOR NAVIGATION
29 Nov. – 2 Dec. 2021, Lloret de Mar, Spain

!

- Only treadmill walking
- No irregular activities
- Sensor placed in hand (wrist placement can be different)
- Only on young adults

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Conclusions and Future work

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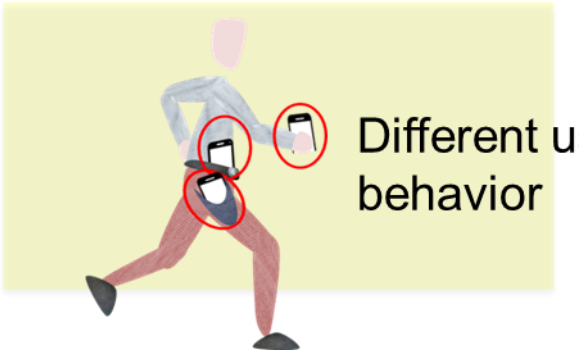
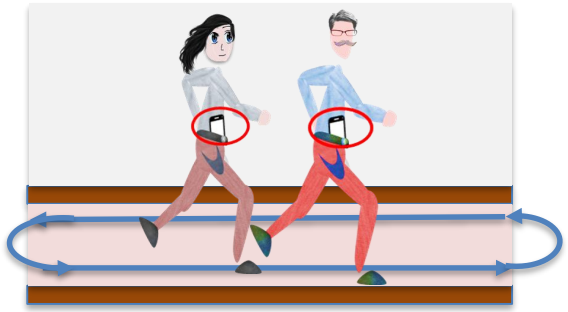
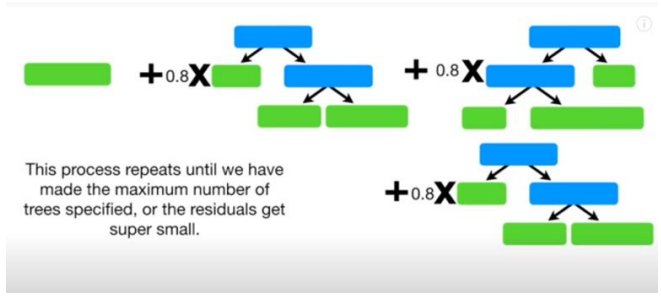
Conclusions



We were able to measure stride time variability with a good precision for different phone handling positions



Created a phone IMU recording app and were able to record 6MWT at Hospital and extract data



Promissing results from machine learning for step detection

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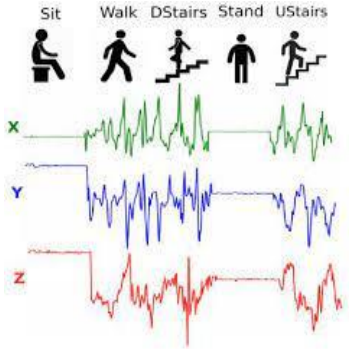
Future work

Enlarge dataset to include many cases for machine learning model



Different activities

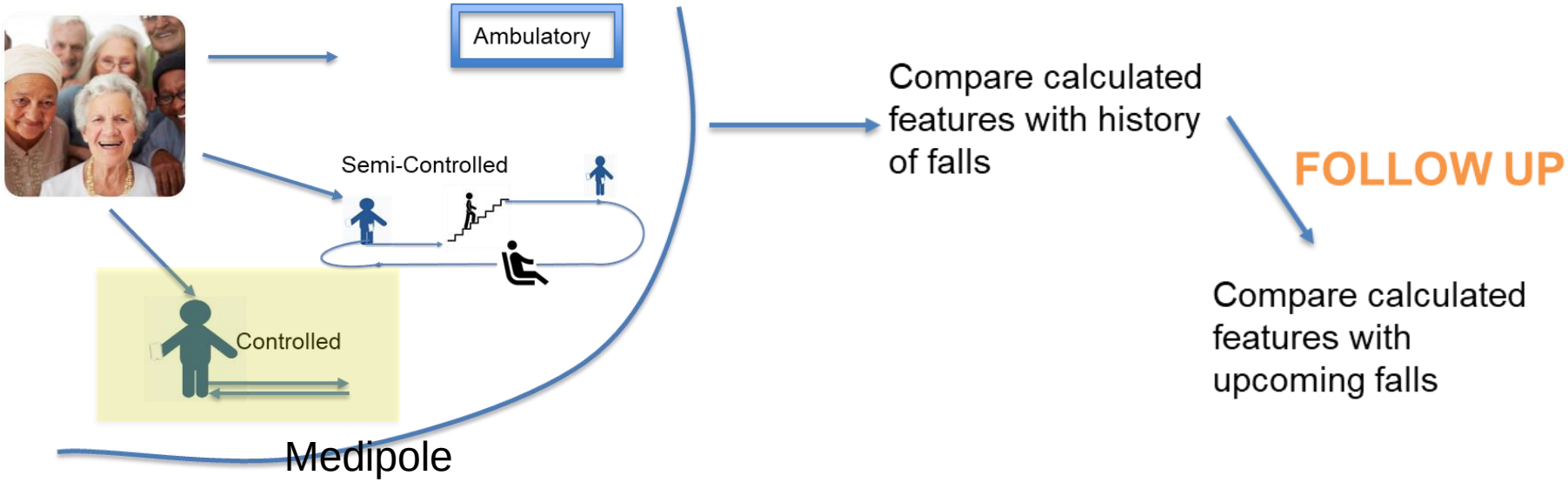
Different walking environments

Add population

Use online databases
Medipole experiment data

Future work

Include more elderly population and follow up phases.



We want to get to ambulatory assessments

Thank you for listening

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Laboratoire de Biomécanique et Mécanique des Chocs
(LBMC UMR_T 9406, UCBL-Univ Eiffel), Lyon

ou pour la version anglaise

Biomechanics and Impact Mechanics Laboratory
Univ Lyon – Univ Eiffel, France

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