PSI3542 2023
SISTEMAS EMBARCADOS DISTRIBUIDOS

Aula 04 – Trabalho 1 Detecção de Queda de Idosos

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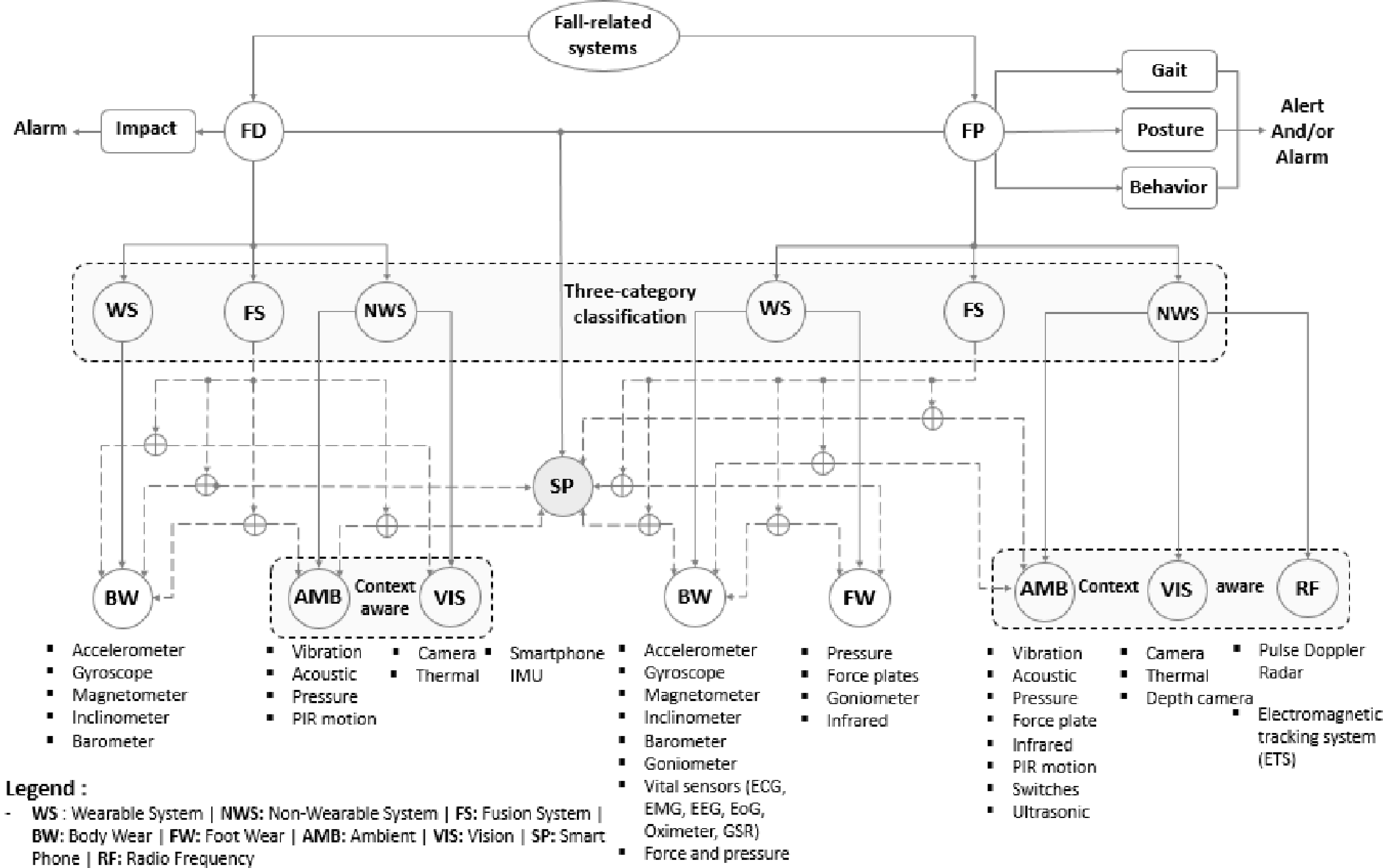
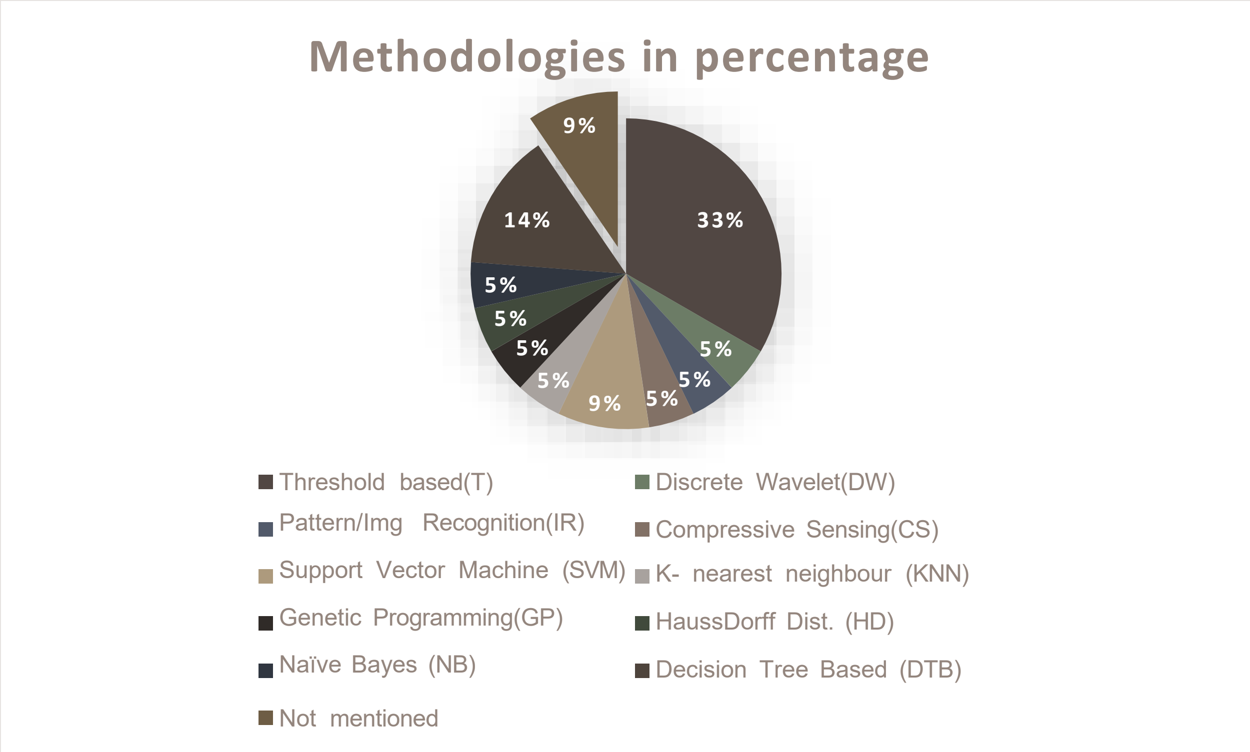
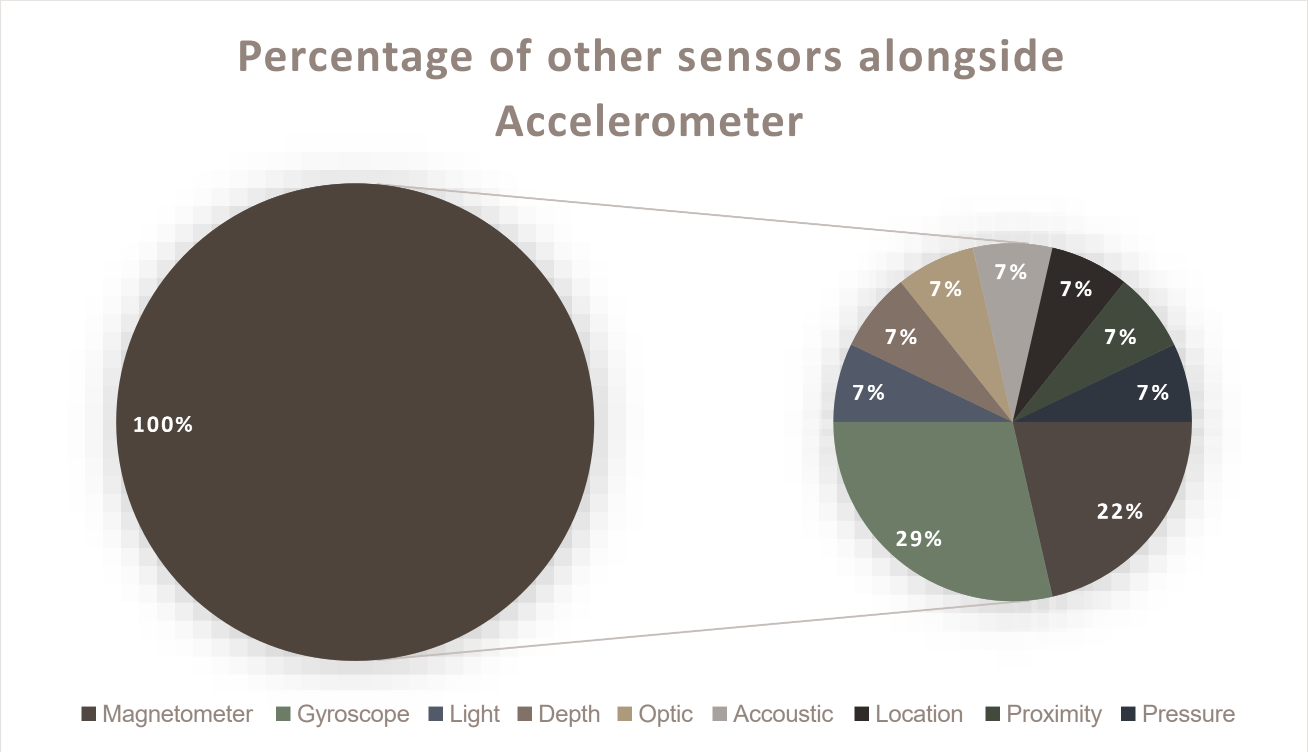
Trabalho 1 – Detecção de queda de idosos com smartphone como dispositivo IoT

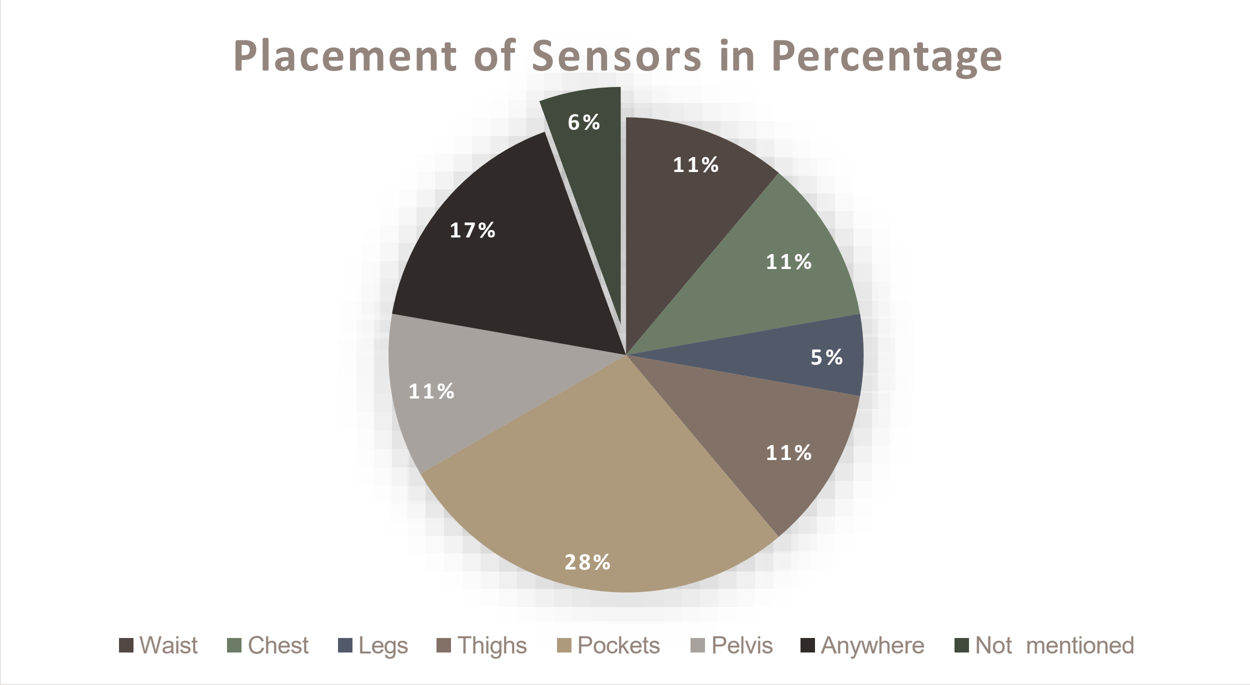
- Requisitos Iniciais
  - Idosos
  - Ambiente doméstico interno (Intradoor)
  - Smartphone com sensor acelerômetro

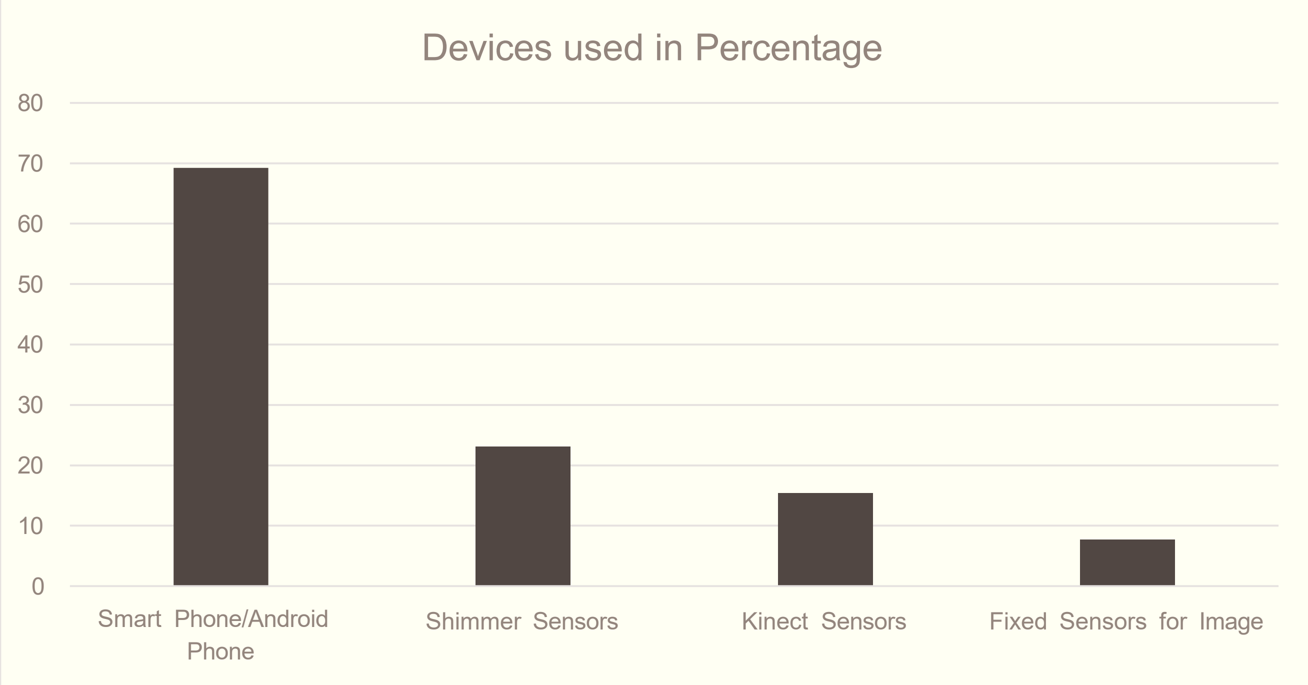

Fall-related systems
Alarm
Impact
FD
FP
Gait
Posture
Behavior
Alert And/or Alarm
Three-category classification
WS
FS
NWS
WS
FS
NWS
SP
BW
AMB
Context aware
VIS
BW
FW
AMB
Context
VIS
aware
RF
Accelerometer
Gyroscope
Magnetometer
Inclinometer
Barometer
Vibration
Acoustic
Pressure
PIR motion
Camera
Thermal
Smartphone IMU
Accelerometer
Gyroscope
Magnetometer
Inclinometer
Barometer
Goniometer
Vital sensors (ECG, EMG, EEG, EoG, Oximeter, GSR)
Force and pressure
Pressure
Force plates
Goniometer
Infrared
Vibration
Acoustic
Pressure
Force plate
Infrared
PIR motion
Switches
Ultrasonic
Camera
Thermal
Depth camera
Pulse Doppler Radar
Electromagnetic tracking system (ETS)
Legend :
- WS : Wearable System | NWS: Non-Wearable System | FS: Fusion System | BW: Body Wear | FW: Foot Wear | AMB: Ambient | VIS: Vision | SP: Smart Phone | RF: Radio Frequency

Caractyerização do Problema

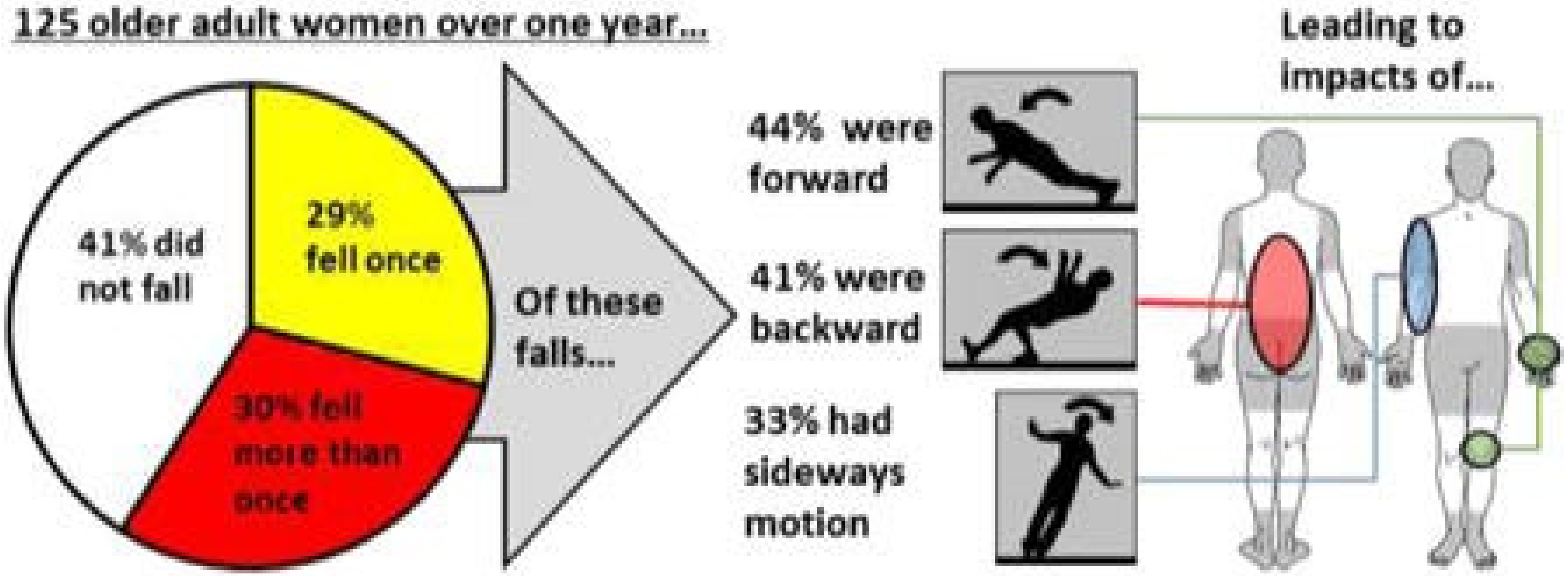

Methodologies in percentage
9%
33%
14%
5%
5%
5%
5%
5%
5%
9%
5%
Threshold based(T)
Discrete Wavelet(DW)
Pattern/Img Recognition(IR)
Compressive Sensing(CS)
Support Vector Machine (SVM)
K- nearest neighbour (KNN)
Genetic Programming(GP)
HaussDorff Dist. (HD)
Naïve Bayes (NB)
Decision Tree Based (DTB)
Not mentioned


Percentage of other sensors alongside Accelerometer
100%
7%
7%
7%
7%
7%
7%
7%
22%
29%
Magnetometer
Gyroscope
Light
Depth
Optic
Accoustic
Location
Proximity
Pressure


Placement of Sensors in Percentage
6%
11%
17%
11%
5%
11%
11%
28%
Waist
Chest
Legs
Thighs
Pockets
Pelvis
Anywhere
Not mentioned

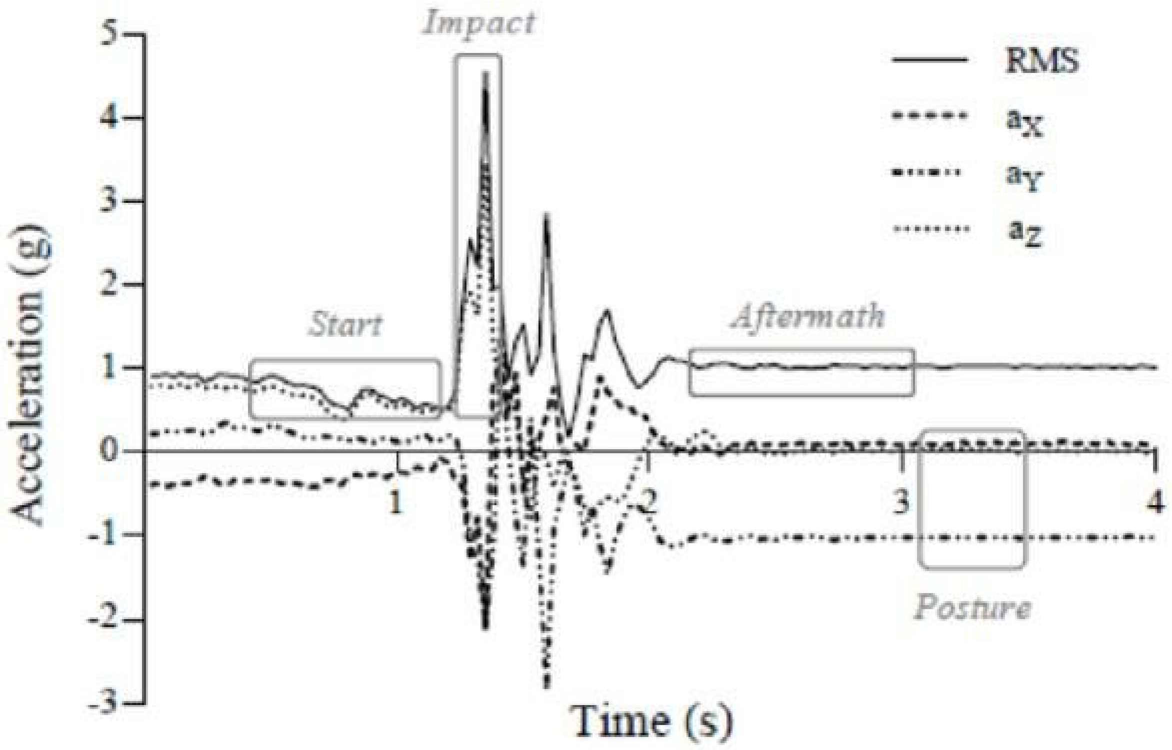

Devices used in Percentage
80
70
60
50
40
30
20
10
0
Smart Phone/Android Phone
Shimmer Sensors
Kinect Sensors
Fixed Sensors for Image

Oreintação de Quedas de Idosas



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5858880/

Caracterização de Queda



[Acceleration Changes during an accidental fall [12] | Download Scientific Diagram (researchgate.net)]

Revisão da Literatura

LITERATURE REVIEW

Publication	*Methodologies*	*Devices Used*	*Members*	*Placement*	*Parameters*	*Type of Device*
(Sposaro & Tyson, 2009)	Threshold Based	Android phone	N/A	anywhere	Accelerometer	SINGLE
(Tacconi, et al., 2011)	Threshold Based	Smartphone	3 (young healthy;24-26)	waist	Tri-axial accelerometer	SINGLE
(Dai, et al., 2010)	Threshold Based , Shape Context and Hausdorff Distance	Smartphone	Dummy + 15 (young student; 20-30)	Chest, waist, thigh, legs, pant/shirt pockets	Accelerometer, magnetometer	SINGLE
(Yavuz, et al., 2010)	Discrete Wavelet Transformation, Threshold Based	Smartphone	5 healthy	Pocket	Accelerometer	SINGLE
(Brezmes, et al., 2010)	Pattern Recognition, SVM	Smartphone	Not mentioned	anywhere	Accelerometer, magnetometer, light sensor	SINGLE
(Kwolek & Kepski, 2015)	Threshold Based , Image Recognition, Extraction Based, KNN, SVM	Kinect Sensors, Smartphone	5 persons (over 26 yrs.)	pelvis	Accelerometer, depth sensors	MULTIPLE

LITERATURE REVIEW

Publication	*Methodologies*	*Devices Used*	*Members*	*Placement*	*Parameters*	*Type of Device*
(Ojetola, et al., 2015)	Decision Tree Based	Shimmer Sensor	42 volunteers	Chest and thigh	Accelerometer, gyroscope	MULTIPLE
(Dau, et al., 2014)	Genetic Programming, Threshold Based	Smartphone	1(teen male)	Tight/ Loose Pant pockets	Accelerometer, magnetometer, gyroscope	SINGLE
(Rakhman, et al., 2014)	Ubiquitous Based	Smartphone	N/A	Left chest pocket	Accelerometer, gyroscope	SINGLE
(Feldwieser, et al., 2014)	Falls Protocol Based	Shimmer and Kinect Sensor	28(66-89 yrs. elders)	Front pelvis, other fixed regions	Accelerometer, optic and acoustic sensors	MULTIPLE
(Kansiz, et al., 2013)	Decision Tree Based, Naïve Bayes	smartphone	8 subjects	pocket	accelerometer	SINGLE
(Soto-mendoza, et al., 2015)	Decision Tree Based	Smartphone, fixed sensors for acquiring images	19(non participation interview based)	anywhere	Accelerometer, location sensors, proximity, pressure sensors	MULTIPLE
(Neggazi, et al., 2014)	Compressive Sensing	Intel Shimmer	5 (different ages; 22-58)	Not mentioned	Accelerometer, ECG, gyroscope	MULTIPLE

Isabel N. Figueiredo et al. Exploring smartphone sensors for fall detection

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mUX: The Journal of Mobile User Experience

RESEARCH Open Access

Exploring smartphone sensors for fall detection

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Abstract
Falling, and the fear of falling, is a serious health problem among the elderly. It often results in physical and mental injuries that have the potential to severely reduce their mobility, independence and overall quality of life. Nevertheless, the consequences of a fall can be largely diminished by providing fast assistance. These facts have lead to the development of several automatic fall detection systems. Recently, many researches have focused particularly on smartphone-based applications. In this paper, we study the capacity of smartphone built-in sensors to differentiate fall events from activities of daily living. We explore, in particular, the information provided by the accelerometer, magnetometer and gyroscope sensors. A collection of features is analyzed and the efficiency of different sensor output combinations is tested using experimental data. Based on these results, a new, simple, and reliable algorithm for fall detection is proposed. The proposed method is a threshold-based algorithm and is designed to require a low battery power consumption. The evaluation of the performance of the algorithm in collected data indicates 100 % for sensitivity and 93 % for specificity. Furthermore, evaluation conducted on a public dataset, for comparison with other existing smartphone-based fall detection algorithms, shows the high potential of the proposed method.

Keywords: Fall detection, Smartphone, Tri-axial accelerometer, Threshold-based method

Introduction

Statistics and facts related with falls in elderly people is somewhat worrying. For instance, approximately one in every three people, over the age of sixty five, experience a fall, at least once a year, and these are the leading cause of hospitalization for this age group [16]. Another very concerning aspect of falls, among the elderly, is their reluctance to seeking treatment after suffering an injury. Moreover, the economic impact of falls was estimated in 2000 to be $US19 billion in the US only [15]. All of this is even more relevant when one considers that the number of old people (above 60 years old) in the world is expected to increase from 841 million in 2013 to more than 2 billion in 2050 [8].

The previous findings, stress the necessity for healthcare providers to focus on measures to reduce the risk and severity of falls-related injuries. Automatic fall detection

Study of Smartphone Sensor based Fall Detection

Presented by:

Chowdhury Sayef Abdullah & Kawser Ahmed

Department of Electrical & Electronic Engineering

INDEPENDENT UNIVERSITY, BANGLADESH

Supervisor: Dr. Md. Kafiul Islam

Result Analysis (Raw Data)

Events	Minimum	Maximum
Sub 01: Walk and Fall Forward (Fall)	-39.4827	58.8619
Sub 02: Run and Fall (Fall)	-63.4928	20.8167
Sub 01: Upstairs (Non-Fall)	-9.1777	16.5592
Sub 02: Standing to lying position (Non-Fall)	-4.2165	2.1870

Table. Minimum and Maximum from Equivalent Data

Result Analysis (Raw Data) (contd..)

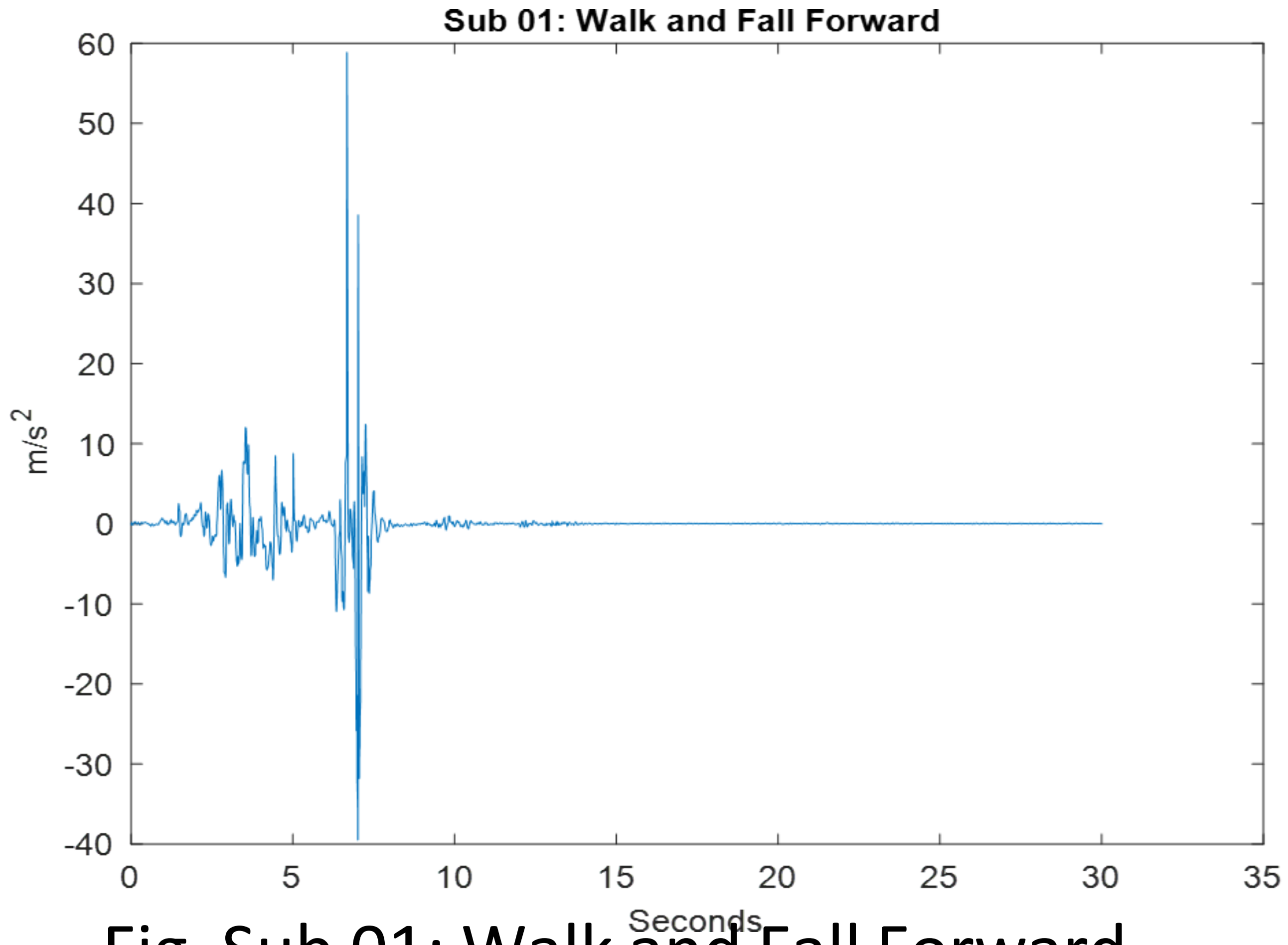

Fig. Sub 01: Walk and Fall Forward (Fall)

*Walked for 5 – 6 seconds

* Impact: At 7 seconds (spike)

* Duration of Fall Event : 1.5 secs

* Completed at 8.5 Sec (Fall)

Result Analysis (Raw Data) (contd..)

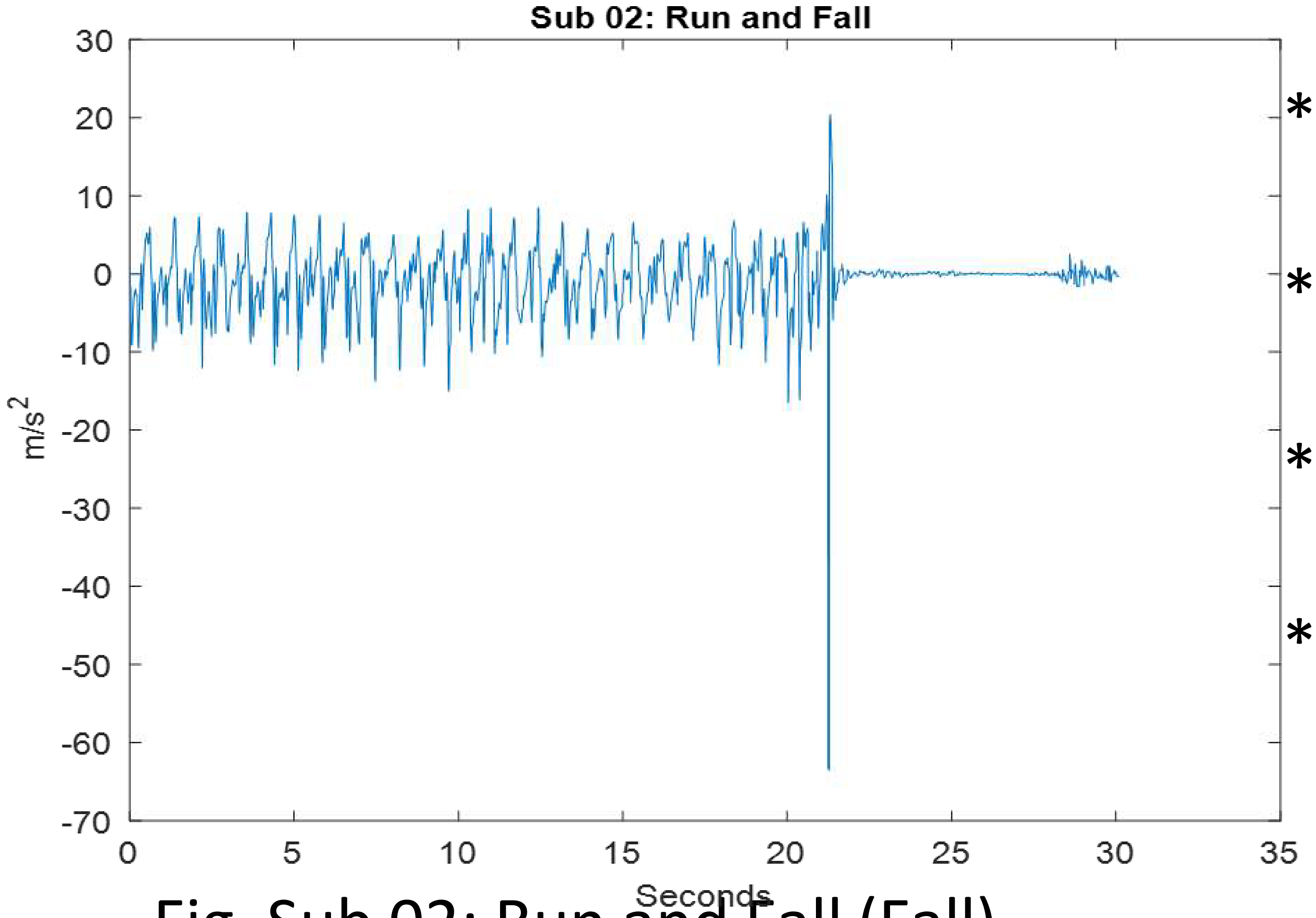

Fig. Sub 02: Run and Fall (Fall)

* Run: 21 seconds

* Impact: At 21.75 seconds (spike)

* Duration of Fall Event : 0.5 secs

* Completed at 22.25 Sec (Fall)

Result Analysis (Raw Data) (contd..)

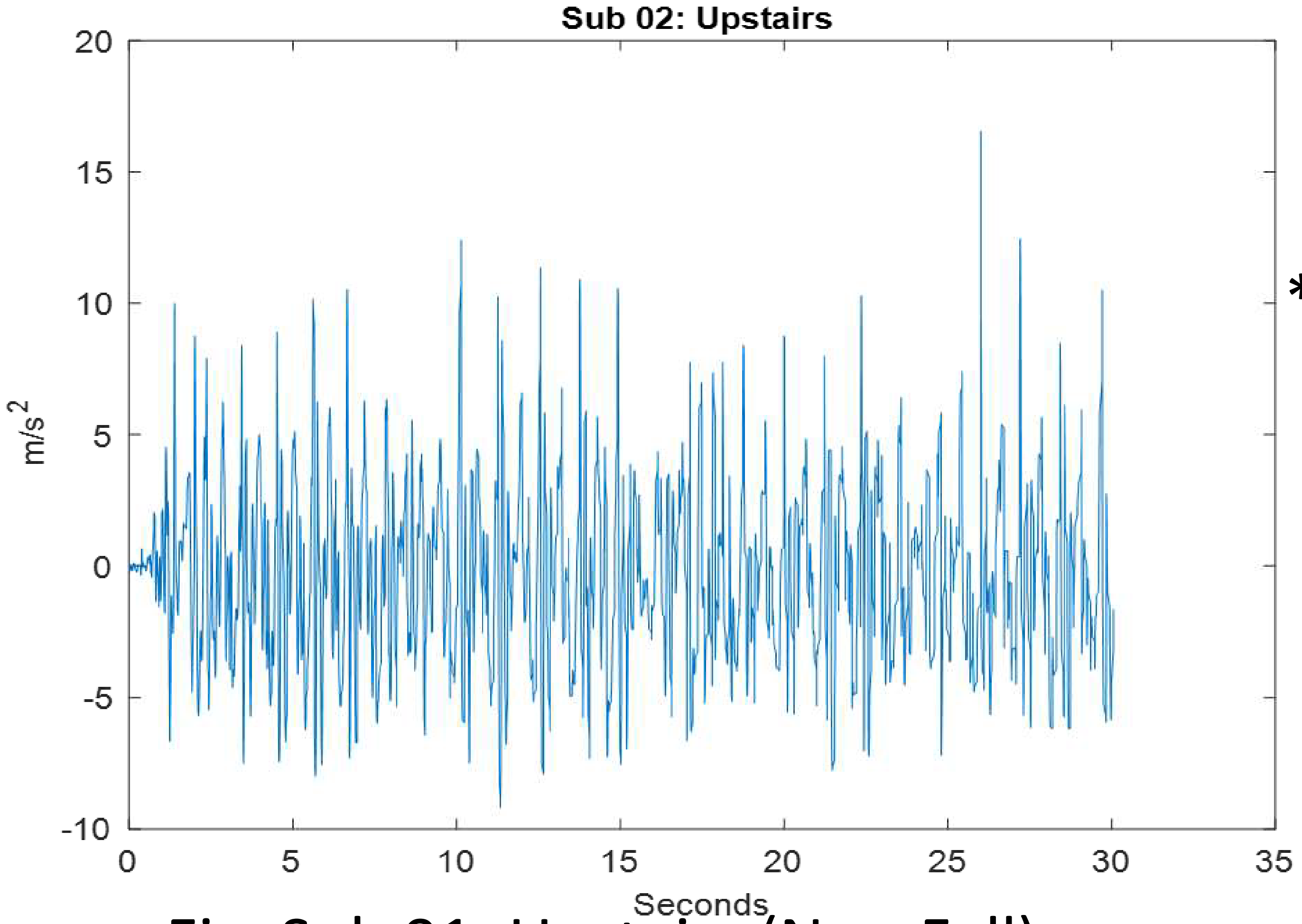

Fig. Sub 01: Upstairs (Non-Fall)

* Stairs : 62 Steps
* Duration of Non-Fall Event : 30 secs

Result Analysis (Raw Data) (contd..)

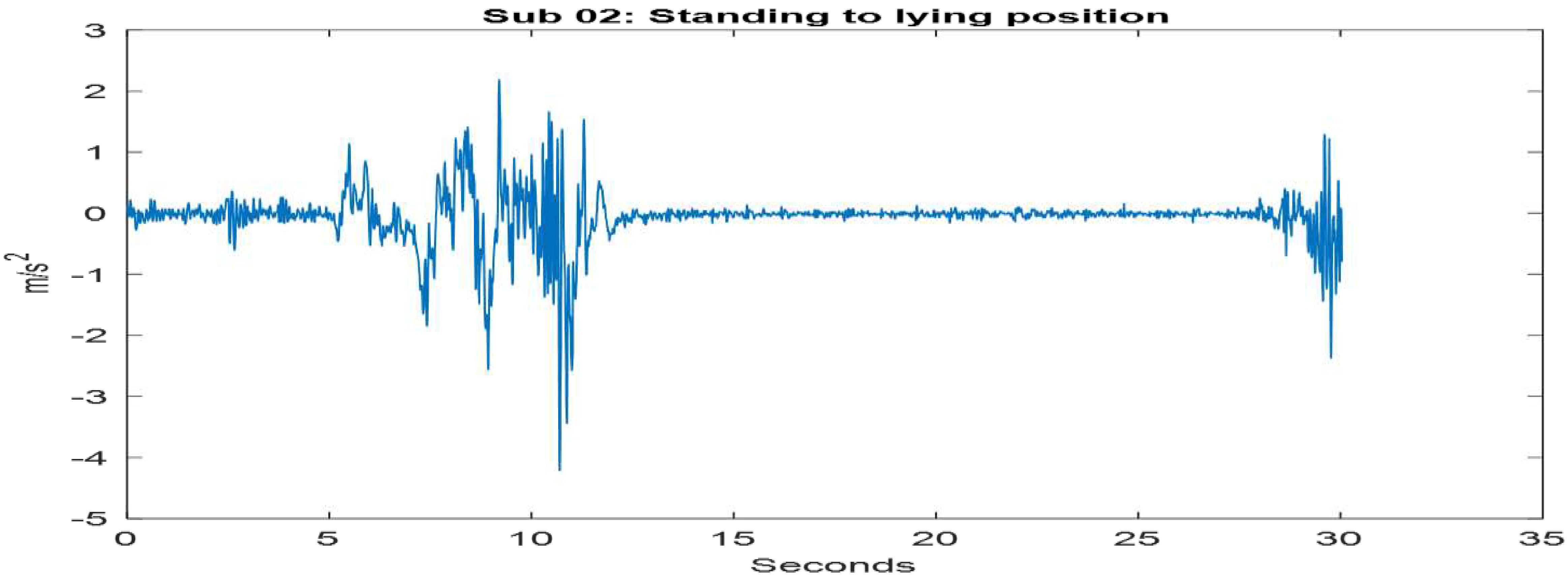

Fig. Sub 02: Standing to lying position (Non-Fall)

Implementação

Implementação

- Fazer a detecção de queda através de dados do sensor acelerômetro, combinado com outros sensores (um ou mais):
  - Velocidade Angular (Giroscópio)
  - Orientação de tela
- Utilizar método simples de detecção: limiar (threshold)
- Usar o Aplicativo Matlab Mobile para aquisição de dados
- Tomar como base as atividades da aula 3 (atividades 3.1. 3.2, 3.3)

Metodologia

- Fazer coletas de dados
  - Máxima taxa de aquisição de dados (10Hz)
  - Obter vários logs misturando
    - quedas em várias posições
    - Andar
    - Correr (?)
    - Sentar e levantar
    - Abaixar
    - Etc

Obrigado

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