



深圳大学
SHENZHEN UNIVERSITY



深圳大学物联网研究中心
The IoT Research Center

G-Fall: Device-free and Training-free Fall Detection with Geophones

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Background



 **60+**
>960 M
(9.6亿)



33%



60%



≈190 million (1.9亿) elders
fall at home each year

2.5% World Population

Existing Methods

Vision

- Kinect
- Camera

Darkness ✗

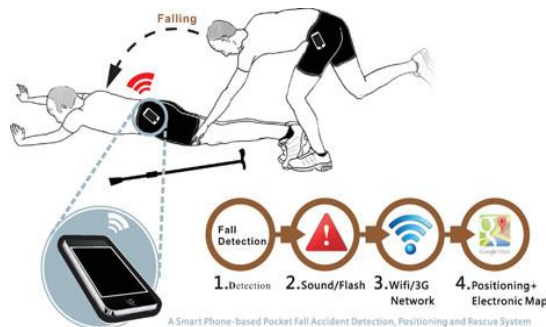
NLOS ✗

Privacy ✗



IMUs

- Gyroscope Obtrusive ✗
- Accelerometer Forgetful ✗



RF

- WiFi (CSI) Training ✗
- False-alarm ✗



Related Work



Accelerometer (SRS) + Microphone (MFCC)
Bayes Classifier



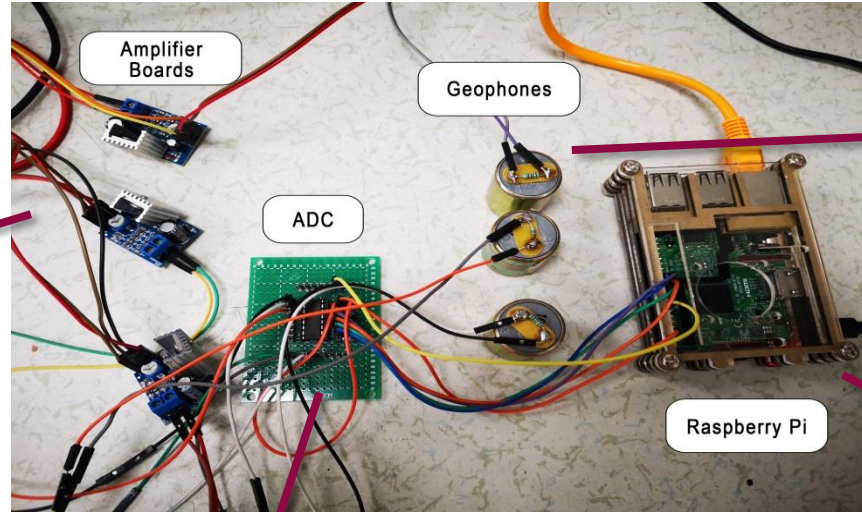
Dataset:
40 drops of human mimicking doll (74 kg)
76 drops of objects and other events.

Prototype

G-Fall Prototype
≈ ¥ 300 (\$45)



**TDA2030A
Amplifiers**



**LGT-20D
Geophones**

**MCP-3008
8-channel 10-bit ADC**

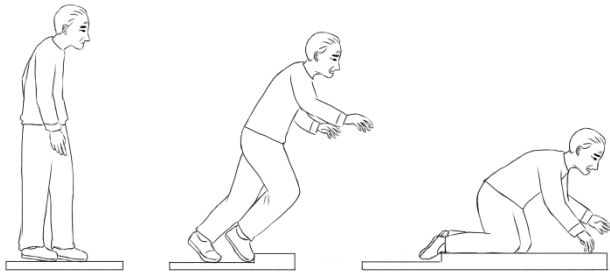


Raspberry Pi 3B

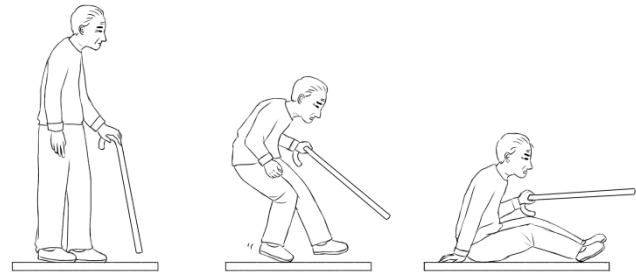


Preliminary study

- i) Physical lesions incur the uncoordinated walking or faint
- ii) falling over the obstacles due to poor vision
- iii) losing balance on a slippery floor such as in a bathroom



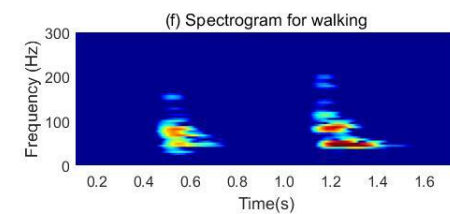
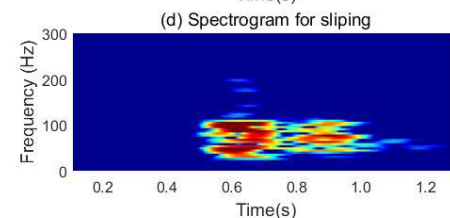
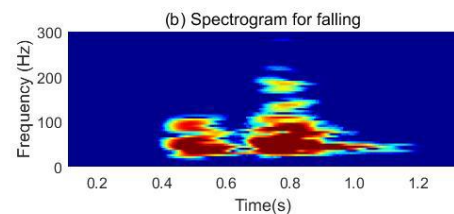
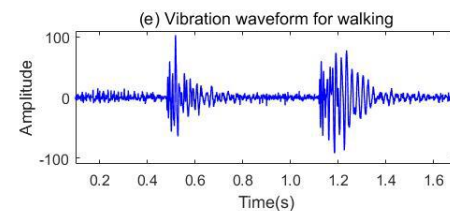
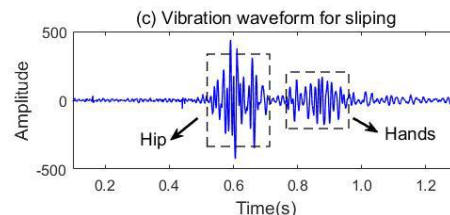
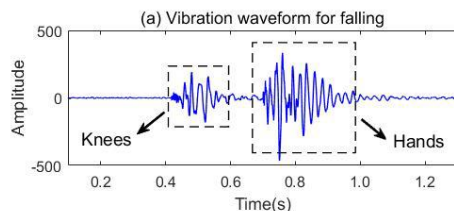
Fall



slip

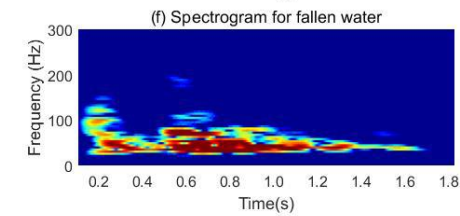
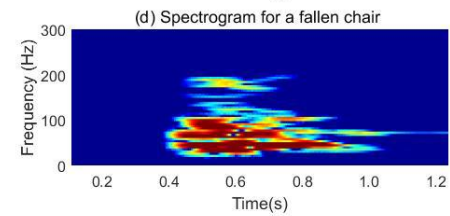
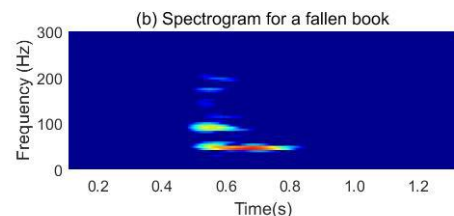
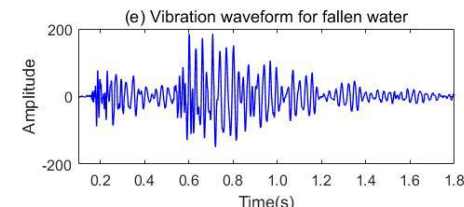
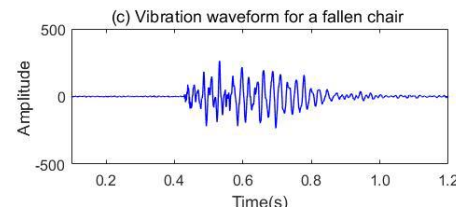
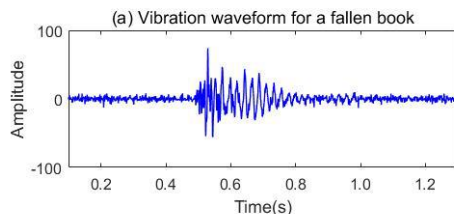
Preliminary study

Body-induced

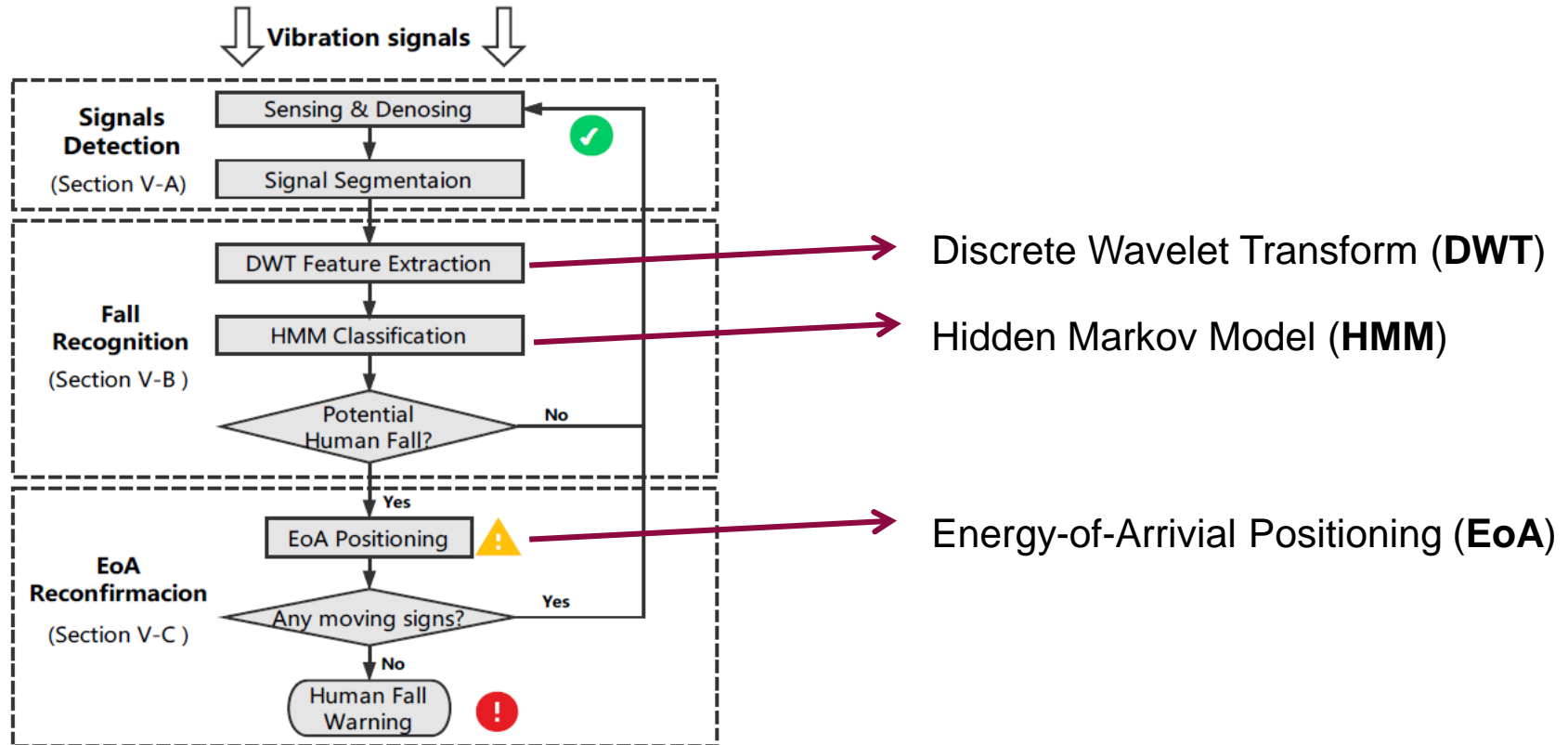


Transition state

Object-induced



Our approach



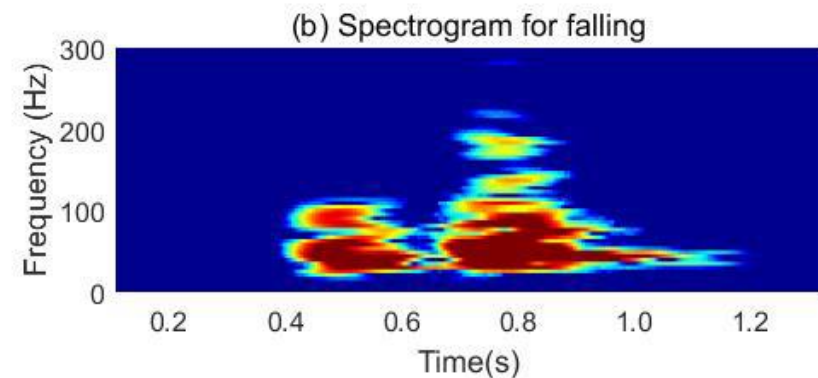
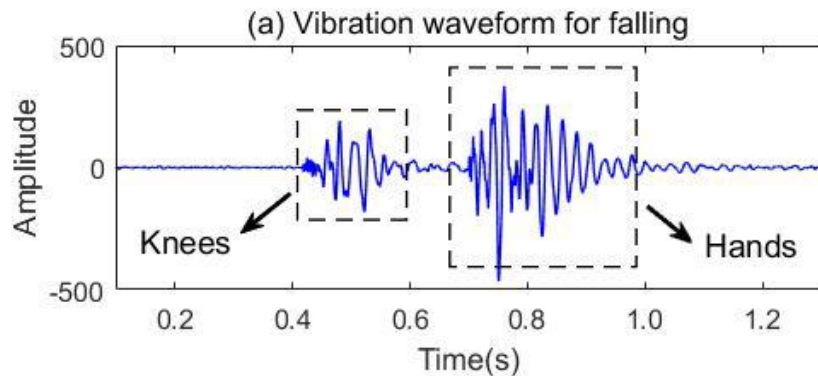
Sensing &
Denosing

Segmentation

Feature
Extraction

Fall
Recognition

EoA
Reconfirmation



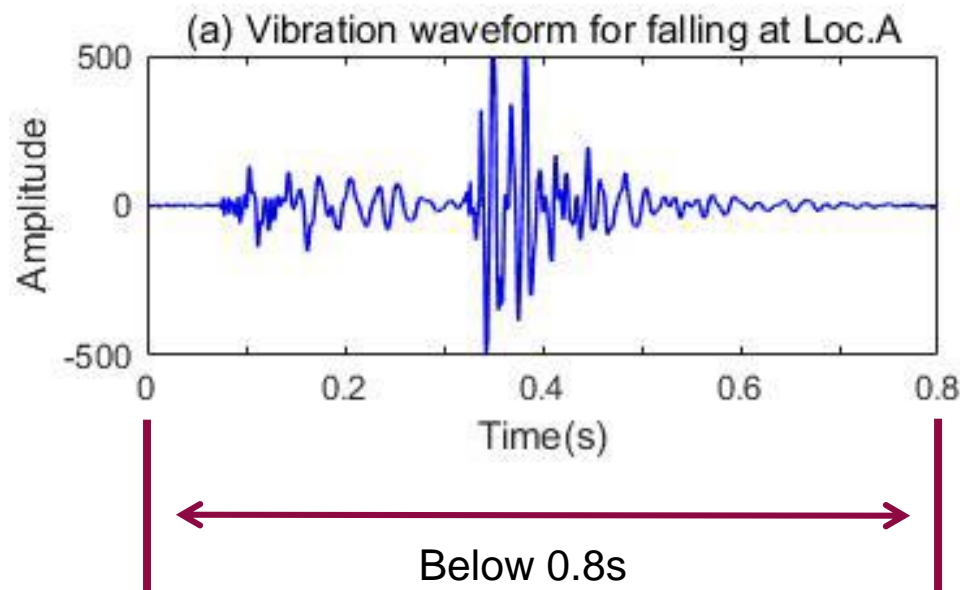
Main components
below 300Hz

Sample rate
1190Hz

Denoising
20Hz High-pass butterworth filter

Sensing &
Denosing

Segmentation

Feature
ExtractionFall
RecognitionEoA
Reconfirmation

Energy-based detection start point

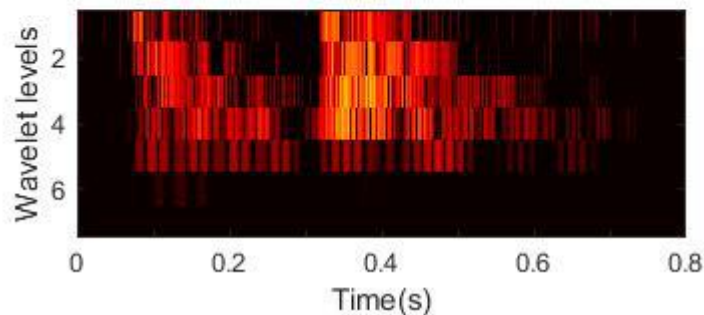
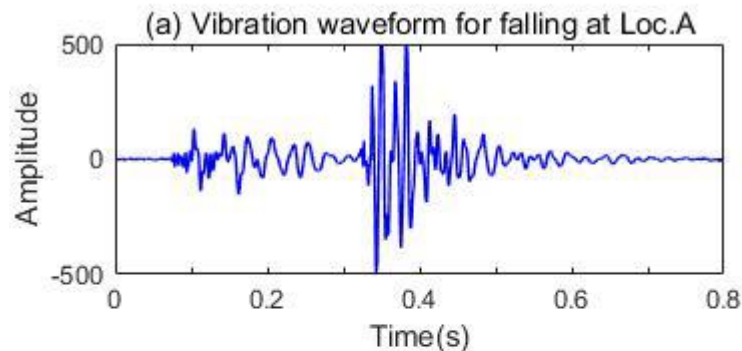
$$E(t) = \sum_{i=t}^{t+L} s^2(i)$$

L: the length of the sliding time window

s(i): the amplitude of the received vibration signals

Sensing &
Denosing

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Discrete Wavelet Transform (DWT)

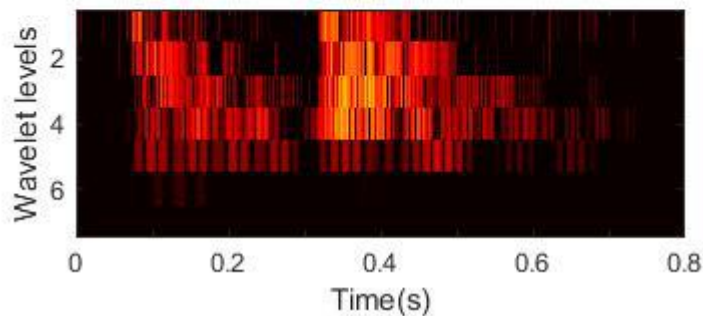
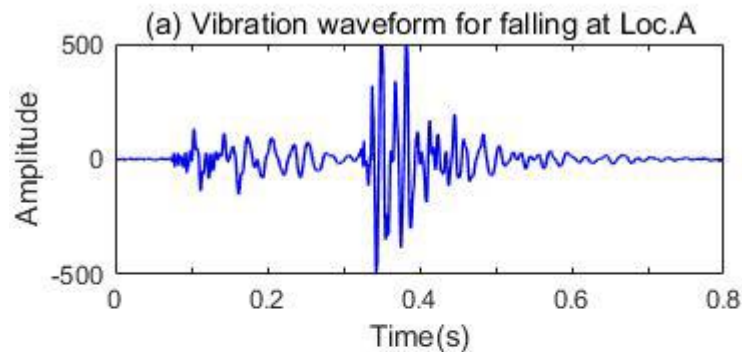
- i) DWT performs a nice tradeoff between time and frequency resolution
- ii) DWT reduces the size of the input sample

Details:

We calculate the energies for 8 levels using Daubechies wavelet in the order of 6 and extracts a 100-dimensional feature vector.

Sensing &
Denosing

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Hidden Markov Model (HMM)

$$\lambda \doteq (A, B, \pi)$$

A: transition probability matrix

B: emission probability matrix

π : initial state vector

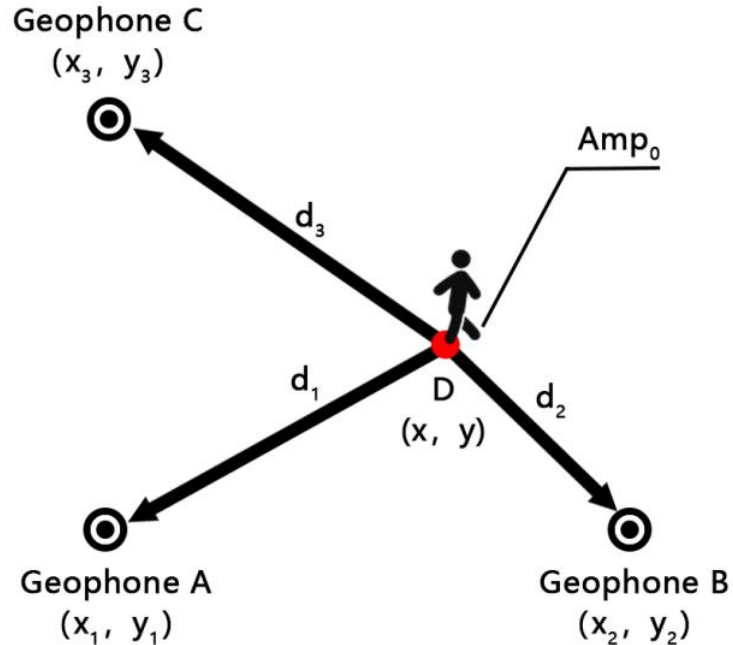
Training: Baum-Welch Algorithm

Sensing &
Denosing

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Energy-of-Arrival (EoA) Localization algorithm



Time Difference of Arrival (TDoA)

- Estimation of accurate time difference
- High sample frequency (65kHz)
- Estimation of signals propagate velocity
- Trouble by Dispersion nature

Energy-of-Arrival (EoA)

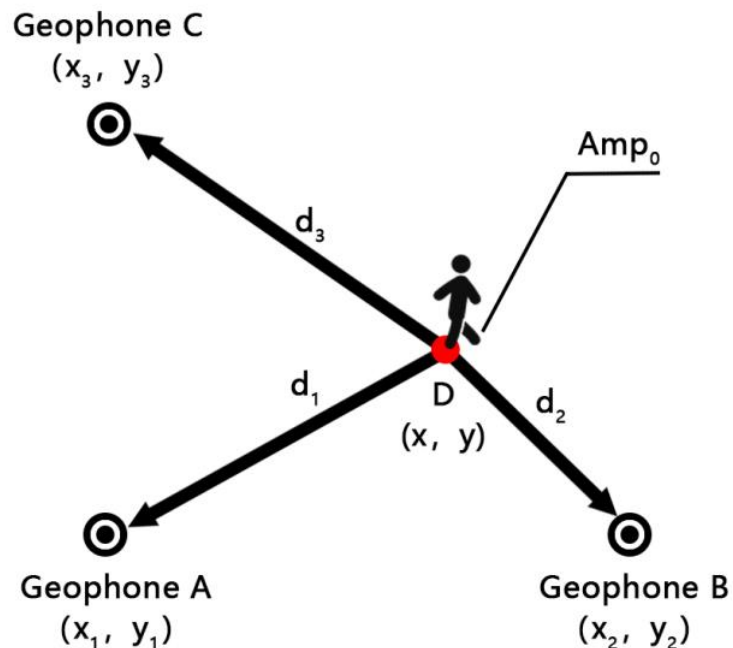
- Estimation of energy of arrival
- Low sample frequency (1190Hz)

Sensing &
Denosing

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Energy-of-Arrival (EoA) Localization algorithm



Attenuation Model:

$$Amp(d) = Amp_0 e^{-\alpha \times d}$$

Amp_0 : the initial amplitude

d : the propagation distance

α : the attenuation coefficient

$Amp(d)$: arrival of amplitude from d

$$A(d_1) = Amp_0 e^{-\alpha \times d_1}$$

$$B(d_2) = Amp_0 e^{-\alpha \times d_2}$$

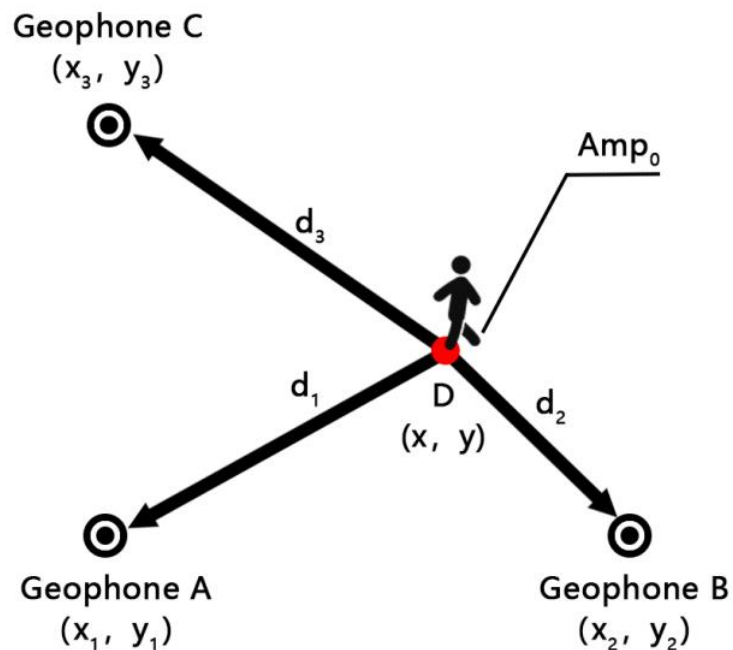
$$C(d_3) = Amp_0 e^{-\alpha \times d_3}$$

Sensing &
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EoA Localization algorithm



$$A(d_1) = Amp_0 e^{-\alpha d_1}$$

$$B(d_2) = Amp_0 e^{-\alpha d_2}$$

$$C(d_3) = Amp_0 e^{-\alpha d_3}$$

Energy ratio:

$$E_{AB} = \frac{A^2(d_1)}{B^2(d_2)} = \left(\frac{Amp_0 e^{-\alpha d_1}}{Amp_0 e^{-\alpha d_2}} \right)^2 = e^{-2\alpha(d_1 - d_2)}$$

$$d_1 - d_2 = \frac{\ln E_{AB}}{-2\alpha} = c_1$$

$$d_1 - d_3 = \frac{\ln E_{AC}}{-2\alpha} = c_2$$



Hyperbola

Evaluation—Setup

TABLE I
The height-weight-age table of the participants

No.	H(cm)	W(kg)	Age	No.	H(cm)	W(kg)	Age
1	178	58	19	7	168	58	21
2	179	57	20	8	181	68	22
3	170	60	26	9	168	58	21
4	177	66	27	10	156	48	20
5	165	61	29	11	168	52	20
6	168	55	20	12	182	59	21

Height(cm)

[156, 182]

Weight(kg)

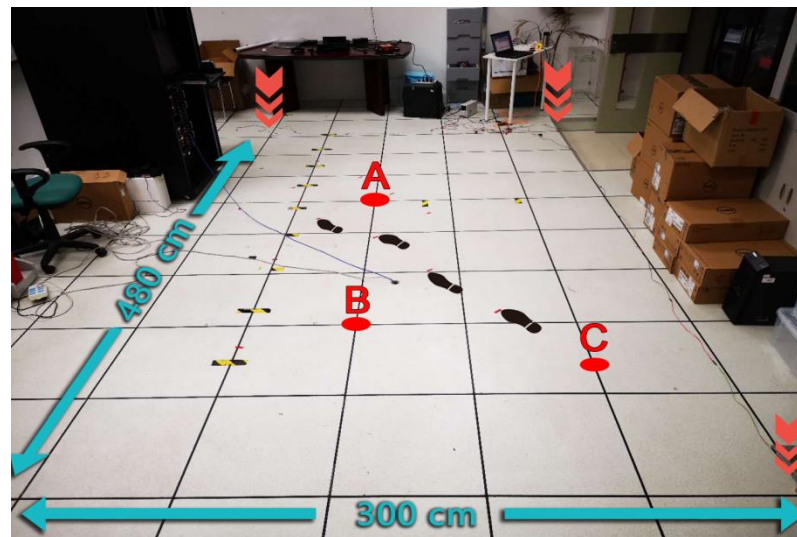
[48-68]

Age

[19-29]

TABLE II
Description of actions for the data collection

Standard Fall	Loc.	Other Actions	Loc.
Trip forward	A	Sit	A
Trip forward	B	Mark time Heavily	A
Trip forward	C	Fall forward from a chair	A
Slip backward	A	Trip forward-Hold on a chair	A
Slip backward	B	Walk normally along the track	Track
Slip backward	C	Walk heavily along the track	Track



$$\text{Precision} = \frac{\# \text{ of truly detected fall}}{\# \text{ of human fall}}$$

$$P_{\text{fls}} = \frac{\# \text{ of wrongly detected fall}}{\# \text{ of other events}}$$

Evaluation——Exp1

➤ Baseline accuracy (one-person training set)

TABLE III
Baseline performance of G-Fall with one person in the training set

Event \ Class. As	Human Fall	Others	Total	Accuracy
Human Fall	495.45	54.55	550	90.08%
Sit	22.68	277.32	300	92.44%
Mark Time	64.05	235.95	300	78.65%
Normal Walk	54.81	1145.19	1200	95.43%
Heavy Walk	227.41	972.59	1200	81.05%
Objects	6.75	68.25	75	91.00%

Training set size enlarge from 5 to 20, the accuracy rise from 80.9% to 94.8%.

Evaluation——Exp1

- Baseline accuracy (one-person training set)

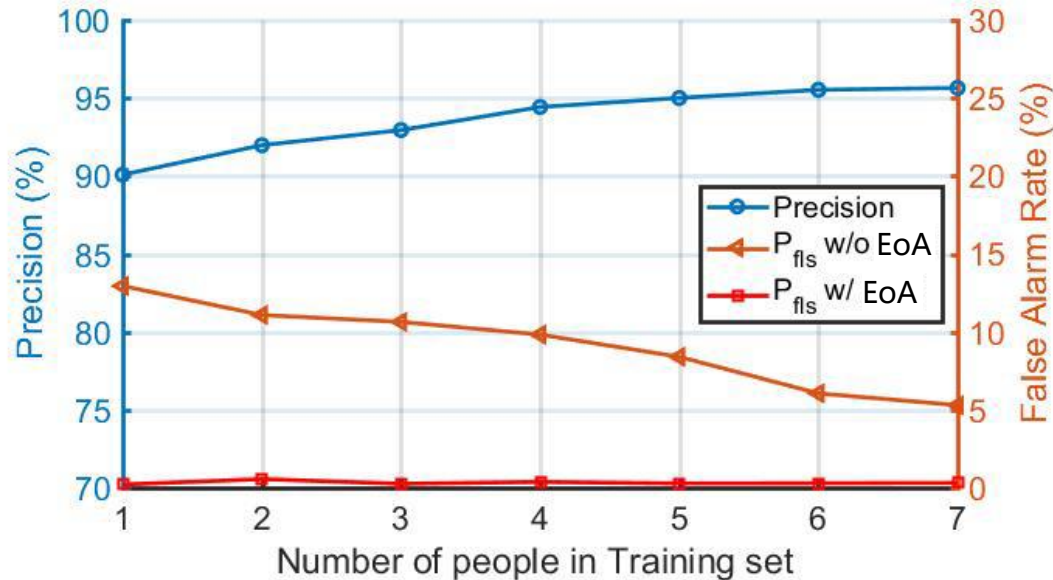
TABLE IV
Comparison of different classifier with one person in the training set

Items	HMM [29]	KNN [35]	SVM [36]	BPNN [37]
<i>Precision</i>	90.08%	83.21%	79.73%	82.08%
<i>P_{fls}</i>	12.30%	17.34%	12.55%	15.70%

HMM provide the best performance

Evaluation—Exp2

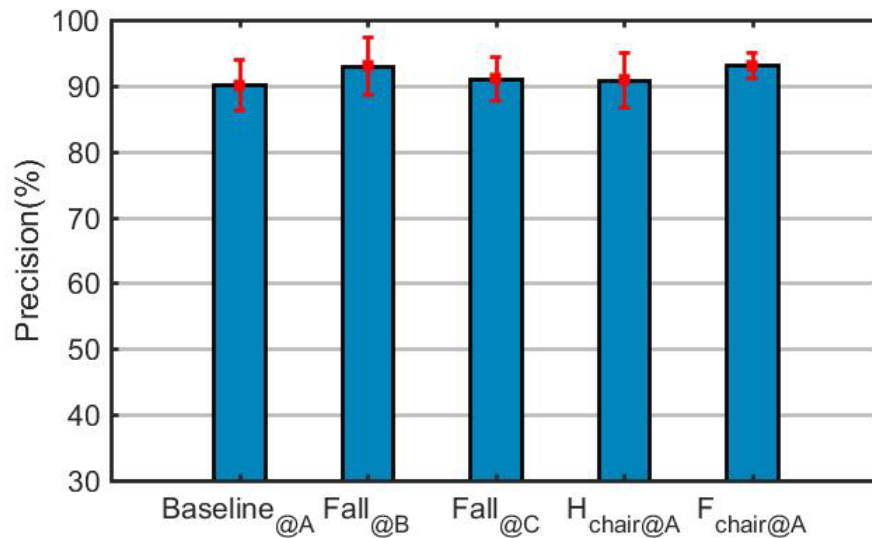
➤ Impact of training set size



Training set size enlarge from one-person to seven-person, the accuracy rise from 90.08% to 95.74%.

Evaluation——Exp3

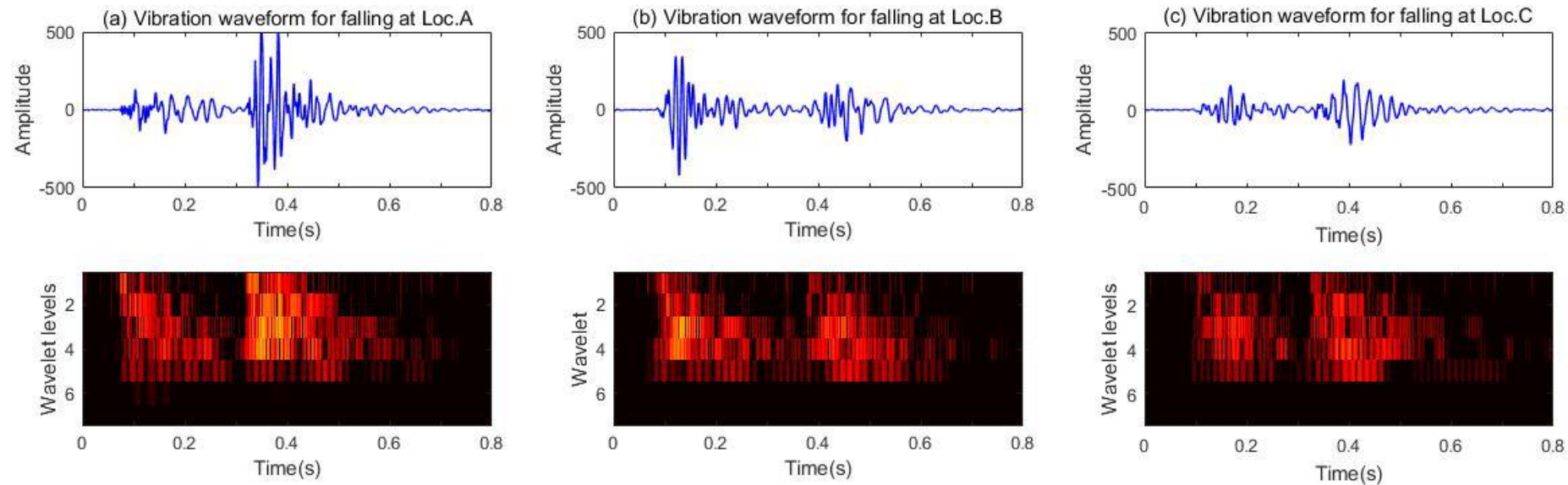
- Impact of different locations



Location independent

Evaluation——Exp3

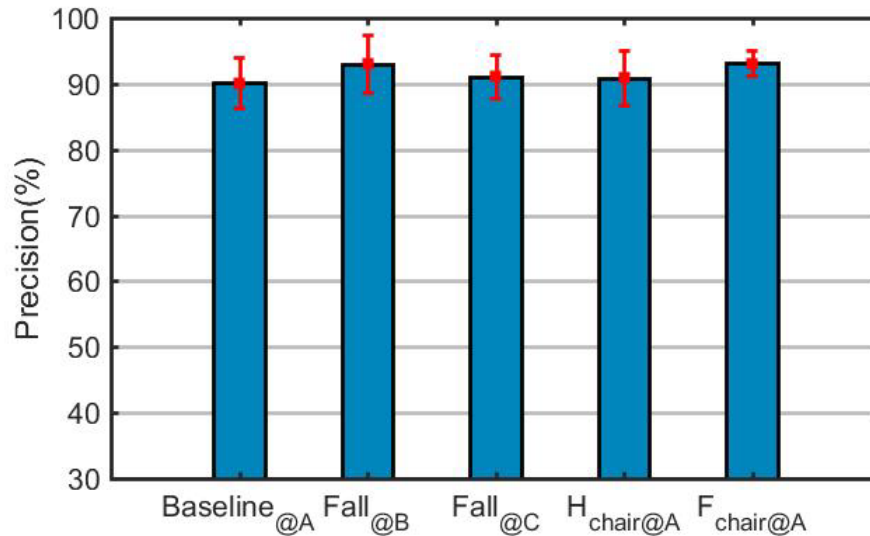
➤ Impact of different locations



Location independent

Evaluation——Exp4

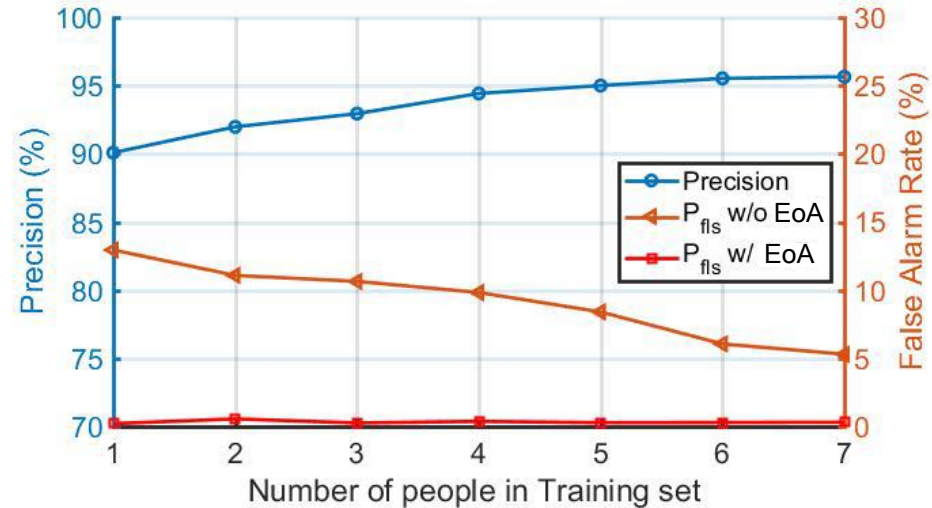
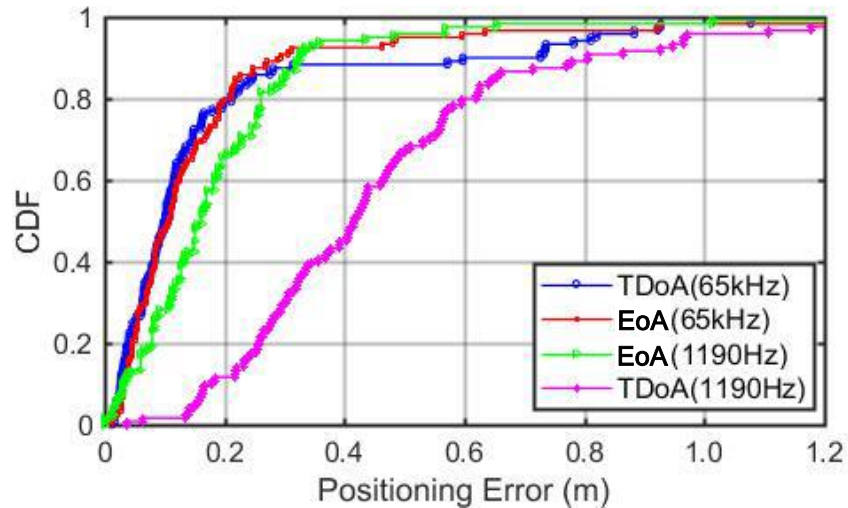
- Impact of non-standard fall



No impact when people perform non-standard fall

Evaluation——Exp5

➤ Effectiveness of EoA



Smaller localization error, and reduce the false alarm to nearly 0%

Conclusion

- G-Fall is the first work to realize a real-time fall detection machine with geophone sensors, achieving a detection precision of 95.74%.
- We propose a reconfirmation mechanism based on Energy-of-Arrival (EoA) localization, the false alarm rate is reduced from 5.30% to nearly 0%.
- G-Fall, is privacy-protected, device-free, training-free, and low false-alarm, which is promising to put into practical use in the future.

Thank you!

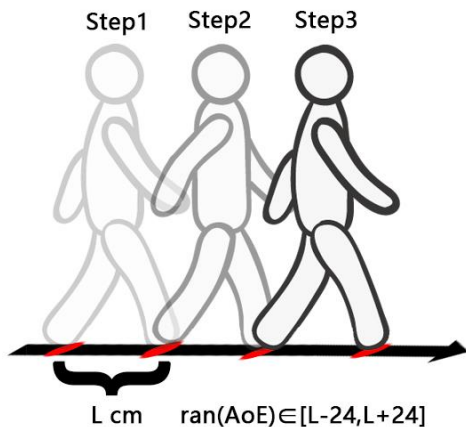


Sensing &
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Detection of moving signs



$$THR = \sum_{i=1}^3 \sqrt{(n_i - n_0)^2 + (m_i - m_0)^2}$$

The estimated coordinate of fall position is $P0(n_0, m_0)$ and that of next three steps is $P1(n_1, m_1)$, $P2(n_2, m_2)$, $P3(n_3, m_3)$