3D Fall Detection and Gait Parameter Identification

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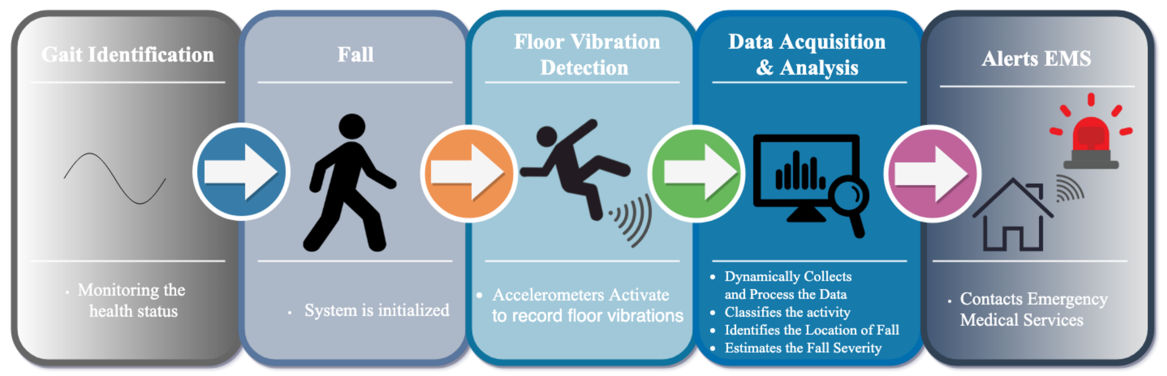
ABSTRACT

Falls and injuries are inevitable for seniors for over sixty-five. Traditional fall detections are good immediate solutions, but they consist of several drawbacks. Our proposed system is able detect and classify falls three-dimensionally and monitor the health status of the patient by studying gait characteristics. Physical experiments were conducted at San Francisco State University to help develop and verify the algorithm being used.

OBJECTIVES



BACKGROUND

- Developed algorithm and physical experimentations were conducted at San Francisco State University.

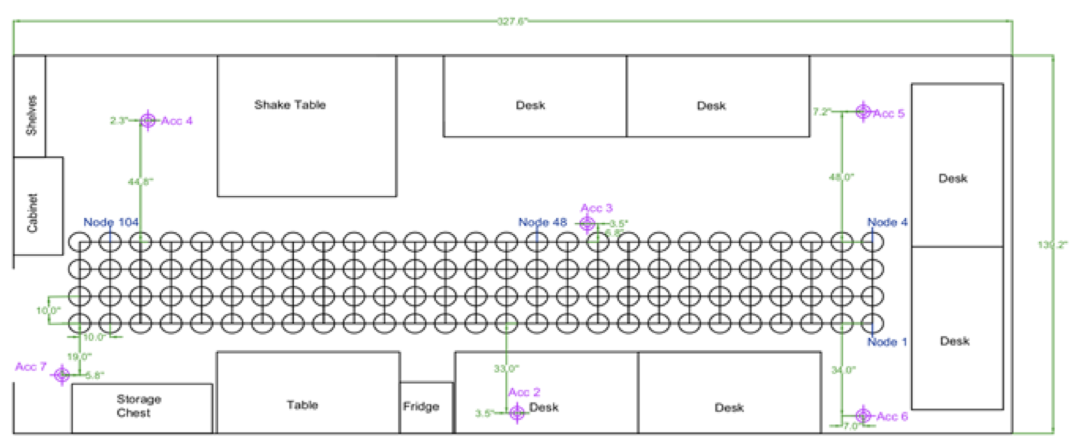


Figure 1: Top down view of the layout of our experiment setup.

- Six accelerometers were placed throughout the mitigation lab to monitor floor vibrations.

Sensor	Model	Serial Number	Sensitivity
Impact Hammer	PCB 086D05	36630	0.23mV/lbf ±15%
Accelerometer 1	PCB 393B31	51836	9.77Vg±5%
Accelerometer 2	PCB 393B31	51835	9.71Vg±5%
Accelerometer 3	PCB 393B31	51820	9.95Vg±5%
Accelerometer 4	PCB 393B31	51815	9.98Vg±5%
Accelerometer 5	PCB 393B31	51819	9.94Vg±5%
Accelerometer 6	PCB 393B31	51814	9.73Vg±5%

Table 1: The list of sensors we used throughout our experiment.

INSTRUMENTATION

Chassis and Devices:
- MATLAB
- Python
- Sensors
  - Accelerometer
  - Impact Hammer
- C Series Sound and Vibration Input Module
  - NI- 9234
- CompactDAQ Chassis
  - cDAQ-9171

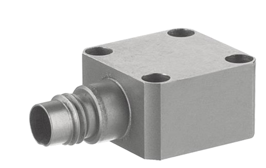
python™ MATLAB

cDAQ-9171

NI-9234

Impact Hammer

Accelerometer



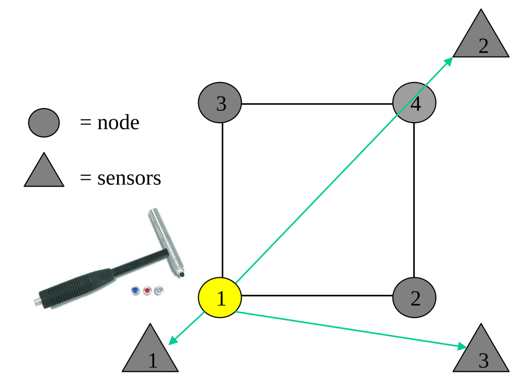
METHODOLOGY

Methodology concepts:

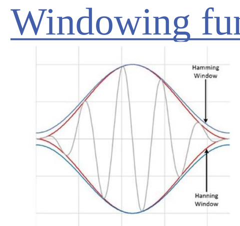
Transfer Function = $TF = \frac{output_{ij}}{input_i}$

$$TFavg_{ij} = \frac{\sum_{n=1}^{n} TF}{n}$$

Force Est. = $input_{ij} = \frac{output_j}{TFavg_{ij}}$



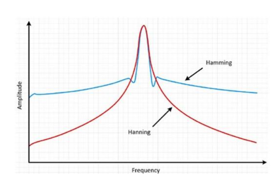
Windowing functions:



- **Hann & Hamming** both have sinusoidal shapes.

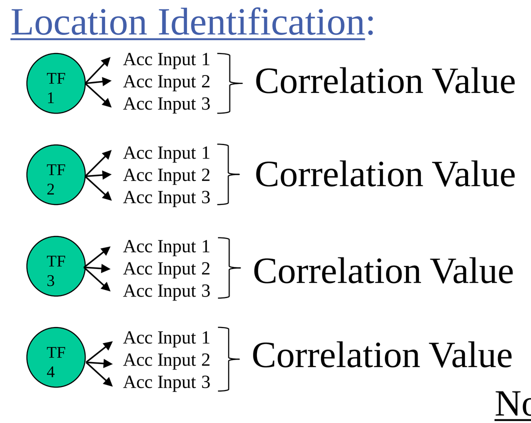
Hann:
- Touch zero at both ends of signals to eliminate discontinuities
- Increases frequency resolution

Hamming :
- does not touch zero
- has slight discontinuity



Kaiser:
- Centers the data in the midpoint

Location Identification:



- Each correlation value takes raw outputs from each accelerometer and compare it to the Average Transfer Function.

$$\boxed{-1 \le Correlation\ value \le 1}$$

Not correlated More correlated

$$\{L_i\} = \max \begin{bmatrix} 0 & \rho_{xy}(\hat{F}_{i,1}(n), \hat{F}_{i,2}(n)) & \cdots & \rho_{xy}(\hat{F}_{i,1}(n), \hat{F}_{i,j}(n)) \\ & 0 & \cdots & \rho_{xy}(\hat{F}_{i,2}(n), \hat{F}_{i,j}(n)) \\ & & \ddots & \vdots \\ \text{sym.} & & & 0 \end{bmatrix}$$

RESULTS

- Total of 791 runs has been recorded throughout this experiment
- Without any windowing functions the statistical measure that associated those transfer functions to the certain nodes had a fair correlation coefficient this is depicted in Table 2.
- After applying Kaiser windowing functions we were successful in increasing the the accuracy of providing vital information about magnitude of where the fall was occurring, this is depicted in Table 3.

Trials	383	100.00%
Exact	7	1.83%
Close	22	5.74%
Moderate	135	35.25%
Fail	219	57.18%

Table 2 : Correlation Coefficient of the Force Est. and Transfer Function.

Trials	32	100.00%
Exact	4	12.50%
Close	13	40.625%
Moderate	14	43.75%
Fail	1	3.125%

Table 3: Correlation Coefficient of the Force Est. and Transfer Function with portion of the data -50,+50.

CONCLUSIONS

- Developed a practical and user-friendly algorithm that is able acquire data dynamically.
- Analyzed the data by running a correlation matrix that compares unique transfer functions to force estimates.
- Applied post processing methods such as Kaiser windowing to increase the accuracy of identifying where the fall has occurred correctly.

FUTURE WORK

- Modeling human activity from structural vibrations to predict oncoming falls.
- Enlarging the spacing of the nodes to 20 inches to improve accuracy of identifying the location.
- Exploring the optimal signal preprocessing for better response time and algorithm.

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