AI-Based Control of Motion Sickness Using Ride Comfort Metrics

Vibration Control and Motion Sickness Mitigation with Neural Networks

Introduction to Motion Sickness in Vehicles

- Motion sickness is caused by conflict between visual, vestibular, and proprioceptive signals.
- In vehicles, high levels of vibration and irregular motion contribute significantly.
- ISO 2631-1 standard defines limits and methods for evaluating ride comfort and health risks.

ISO 2631-1 Ride Comfort Standard

- ISO 2631-1 defines ride comfort using frequency-weighted RMS acceleration:

$$a\_w = \mathrm{sqrt}(1/T * \int a^2(t)\, dt)$$

- RMS acceleration is calculated over a duration (e.g., 60s).
- Lower a_w values indicate better comfort and reduced sickness likelihood.

AI Control Strategy for Vibration Mitigation

- Input: Raw vibration signal from vehicle system (e.g., vertical acceleration).
- Output: Controlled vibration signal via neural network prediction.
- Neural network: MLPRegressor with 1 hidden layer of 50 neurons.
- Trained to minimize output acceleration compared to target damped profile.

Experimental Setup for Simulation

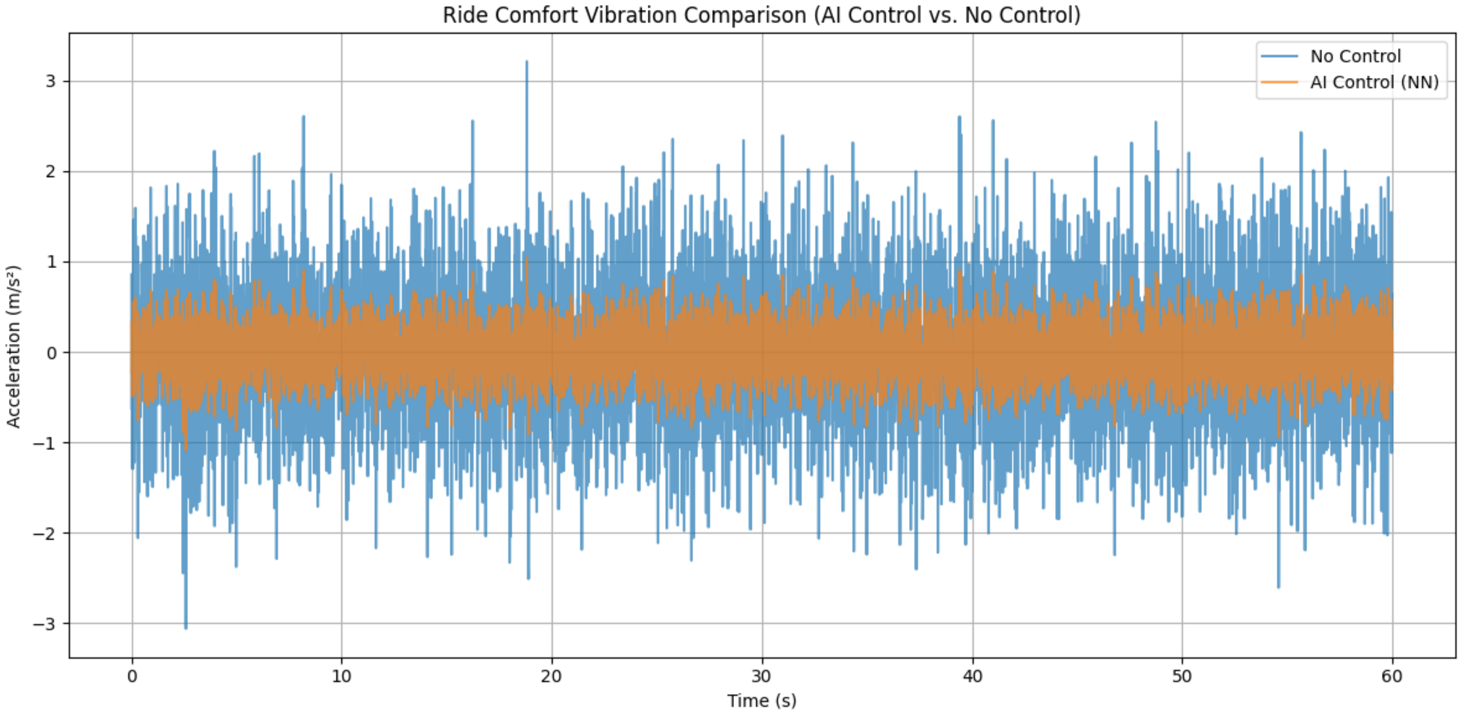
- Duration: 60 seconds, Sampling Rate: 100 Hz
- No control: High amplitude Gaussian noise (σ=0.8)
- AI control: Neural network trained to reduce amplitude

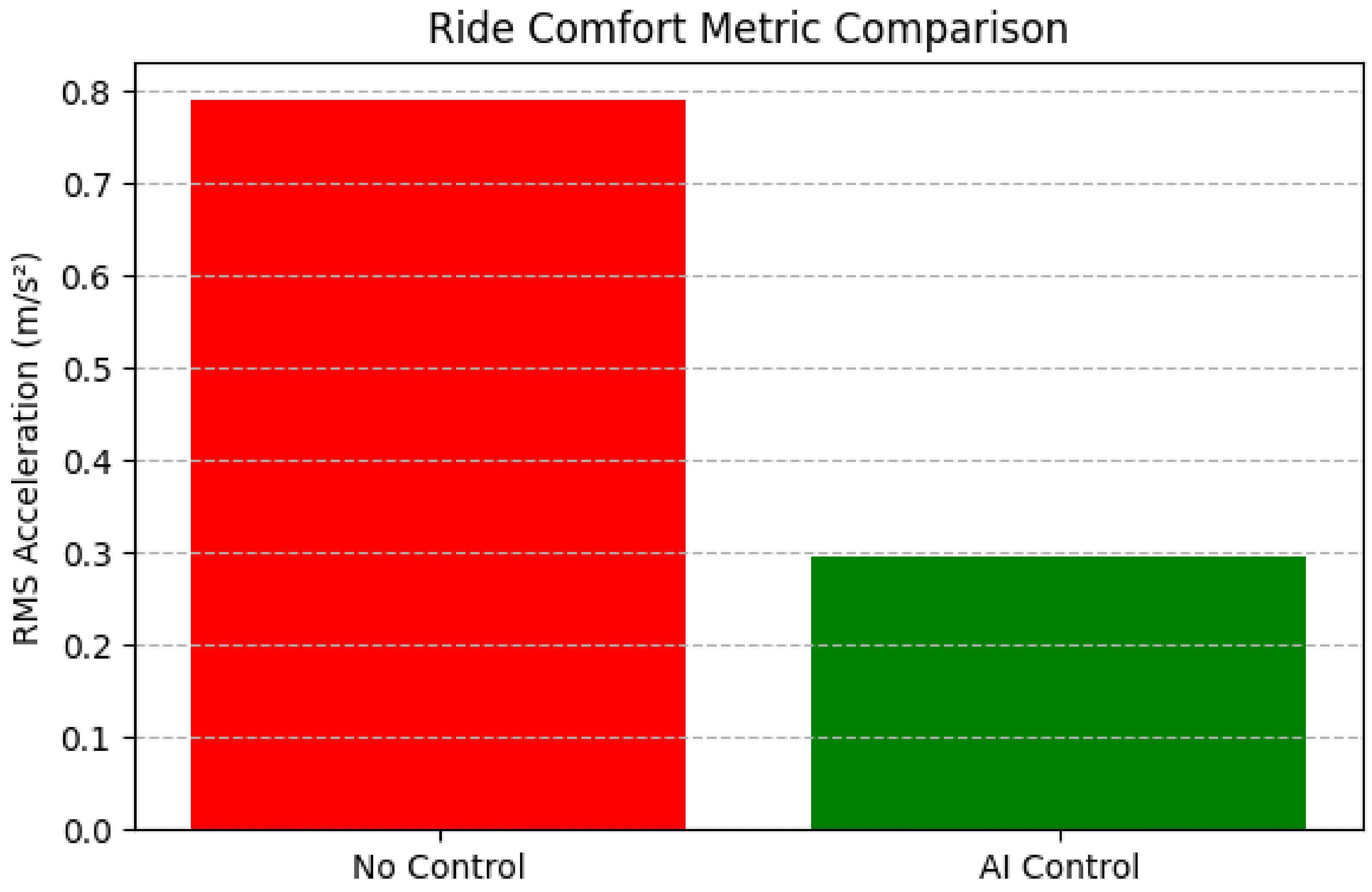
to σ=0.3

- RMS values calculated and plotted for comparison

RMS Acceleration - No Control: 0.791 m/s²

RMS Acceleration - AI Control: 0.297 m/s²




Ride Comfort Metric Comparison
RMS Acceleration (m/s²)
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
No Control
AI Control

Results and Ride Comfort Metric Comparison

- No Control RMS: ~0.80 m/s^2
- AI Control RMS: ~0.30 m/s^2
- AI control significantly reduced vibration amplitude and

improved ride comfort.
- Visual plots show smoother AI-controlled signal over time.

Conclusion and Future Work

- AI-based control using neural networks can effectively mitigate vehicle vibration.
- Reduced RMS acceleration directly corresponds to improved comfort.
- Future work: Extend to real vehicle sensor data and adaptive online learning.

ISO 2631-1: Ride Comfort Levels (RMS Thresholds)

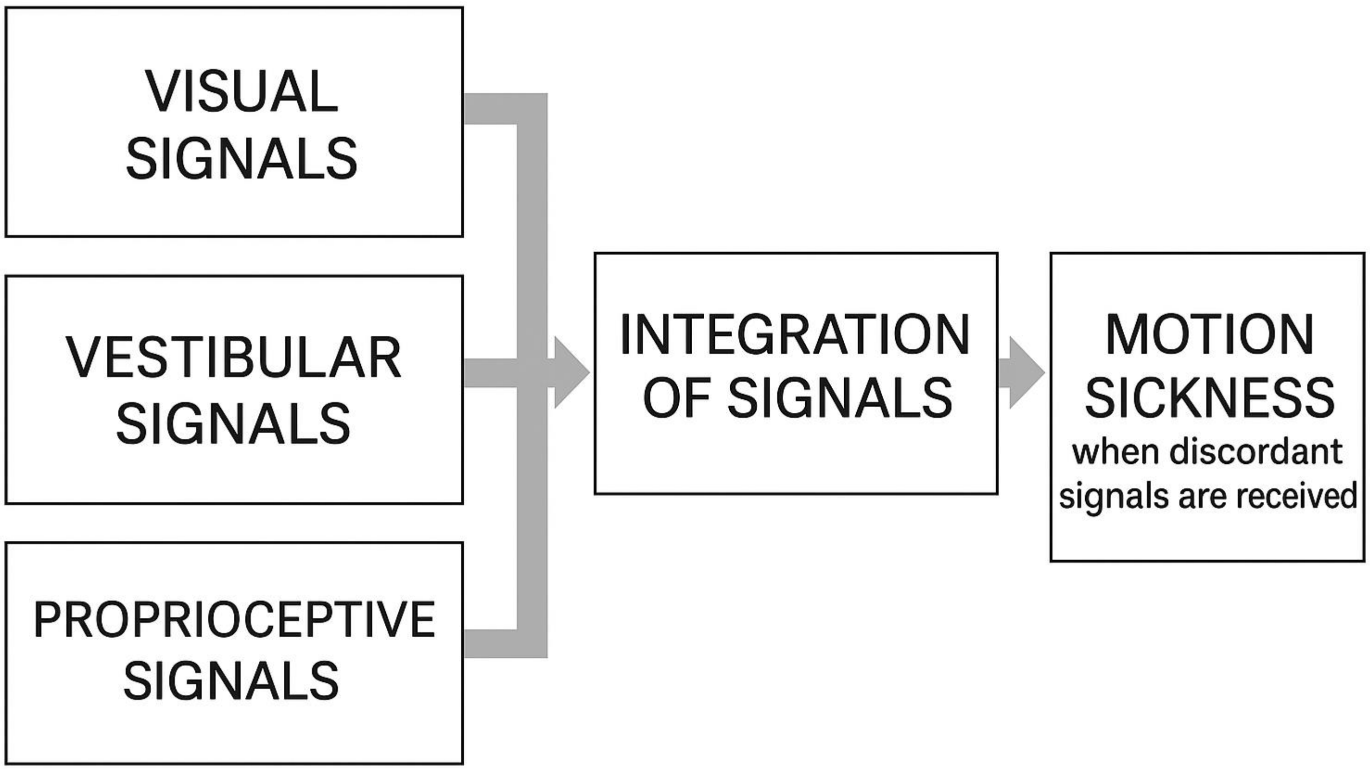
ISO 2631-1 classifies ride comfort based on frequency-weighted RMS acceleration:

- < 0.315 m/s²: Not uncomfortable
- 0.315 – 0.63 m/s²: A little uncomfortable
- 0.5 – 1.0 m/s²: Fairly uncomfortable
- 0.8 – 1.6 m/s²: Uncomfortable
- 1.25 – 2.5 m/s²: Very uncomfortable
- > 2.5 m/s²: Extremely uncomfortable

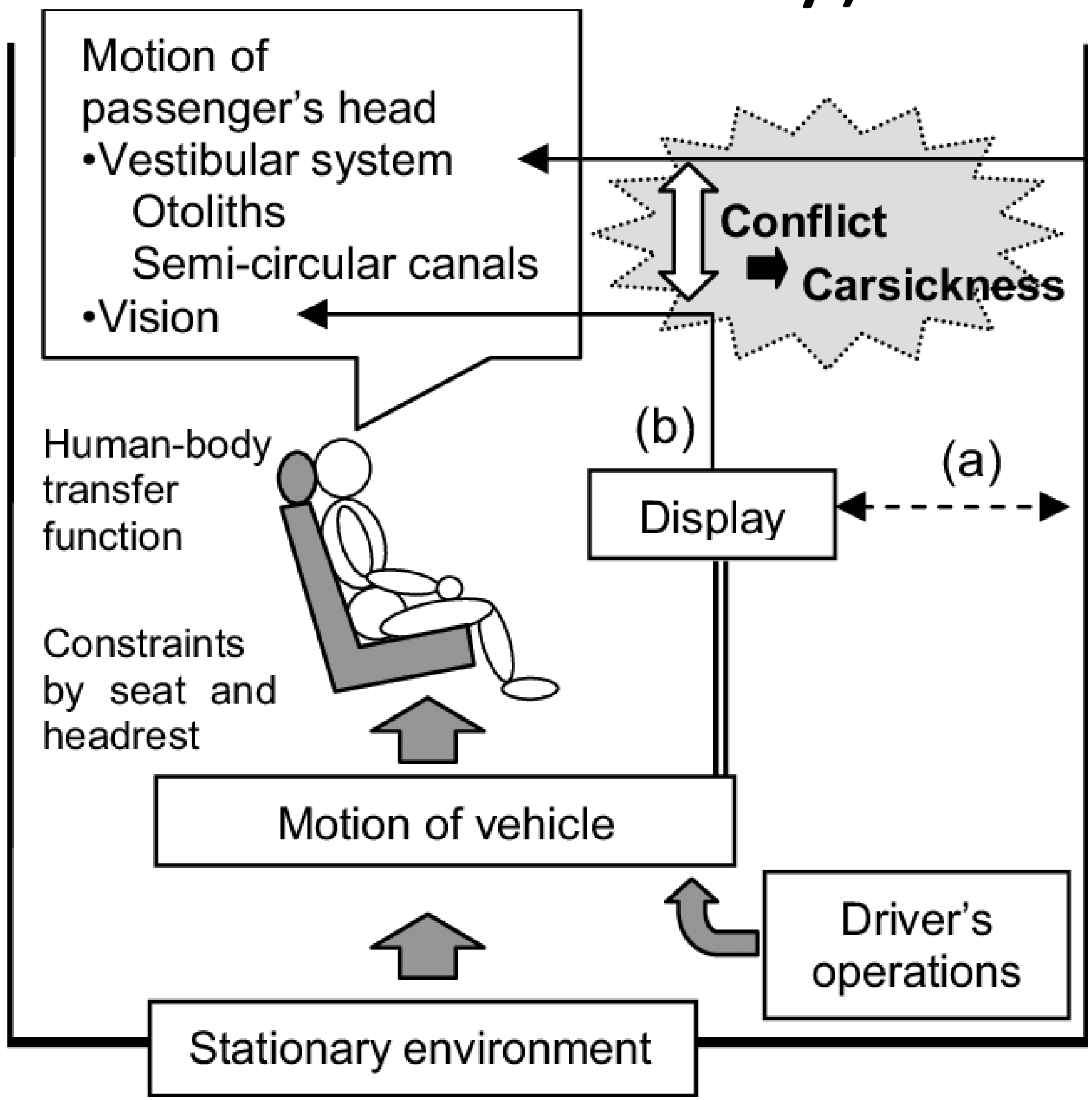
✅ AI control results (~0.30 m/s²) fall into the 'Not uncomfortable' zone.

❌ No control (~0.80 m/s²) is in the 'Uncomfortable' range.

Sensory Conflict Leading to Motion Sickness



Mechanism of Carsickness (Sensory Conflict Theory)



Multilayer Perceptron (MLP) – Definition and Architecture

- A Multilayer Perceptron (MLP) is a type of feedforward artificial neural network composed of input, hidden, and output layers.
- It uses nonlinear activation functions to learn complex mappings from input to output.
- Each neuron computes: $z = W \cdot x + b$, then applies activation: $a = f(z)$
- Common activation: ReLU: $f(z) = \max(0, z)$
- Training is performed using backpropagation with gradient descent.

➤ Used Architecture:

- Input layer: 1 node (raw vibration)
- Hidden layer: 50 neurons, ReLU activation
- Output layer: 1 node (damped output vibration)
- Optimizer: Adam, Epochs: 500

MLP Overview – Equations and Architecture Flow

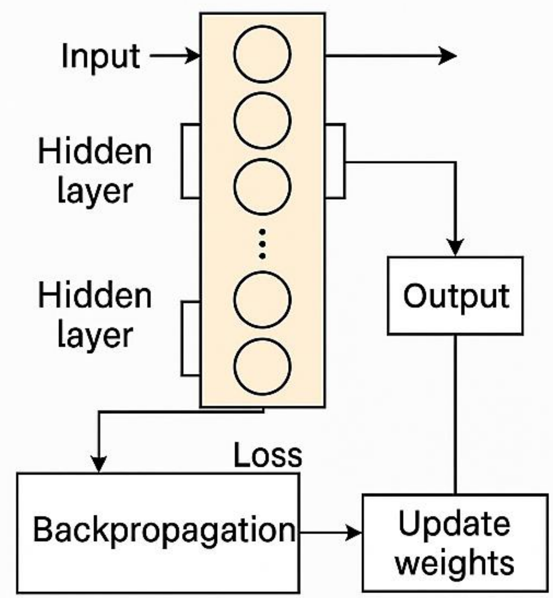
Multilayer Perceptron (MLP)

An MLP is a type of feedforward artificial neural network with multiple layers of neurons.

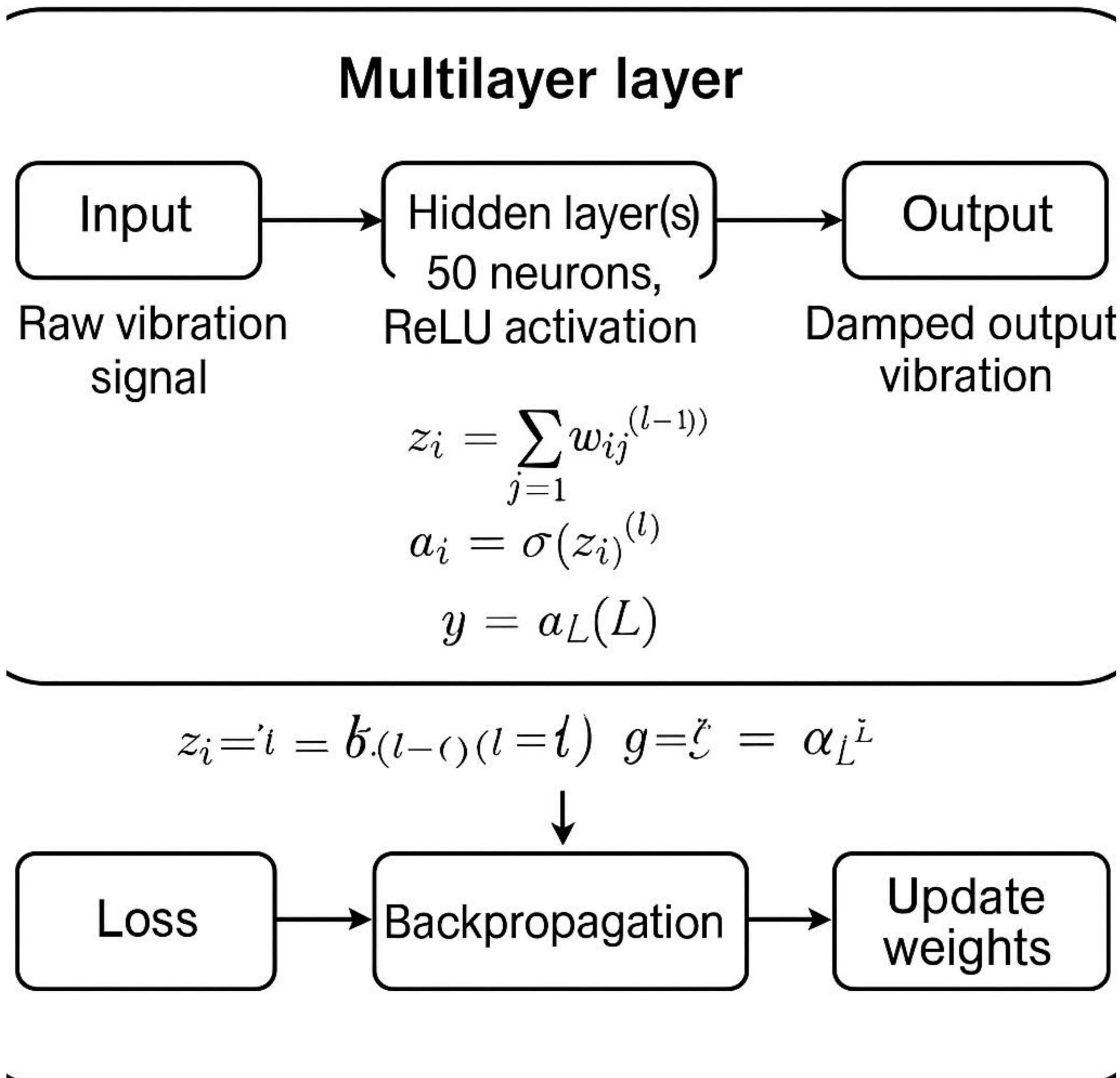
$$z_i^{(l)} = \sum_{j=1}^{n^{l-1}} w_{ij}^{j.(l-1)} + b_i^{(l)}$$

$$a_i^{(l)} = \sigma\left(z_i^{(l)}\right)$$

$$\hat{y} = a_L^{(L)}$$



MLP Architecture and Training Process



MLP Training Process (Forward + Backpropagation)

$$z_i^{(\ell)} = \sum_j w_{ij}^{(\ell)a(-1)} + b_i(\ell)$$

$$a_i = \sigma_i^{(\ell)})$$

$$\dot{y} = a_i^{(L)}$$