ML for Active Noise Control

→ Investigating machine learning architectures for nonlinear systems

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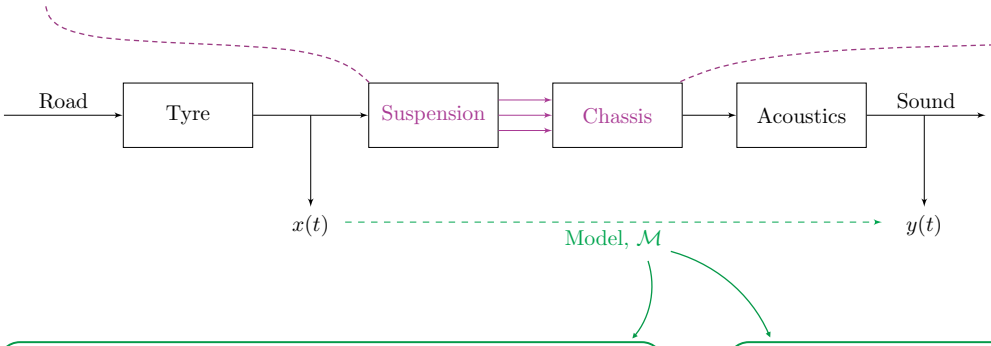
$$f(x,y) = \mu(y-x)^3$$

Motivation

- **Active Noise Control** (ANC) technologies are prevalent and effective in linear systems such as headphones.
- However, ANC for **automotive road noise reduction** is much harder: nonlinearity in suspension systems severely degrades **input-output coherence**, limiting performance.
- Therefore, accurate models are needed to improve ANC reference signals: **machine learning** methods are promising, as they can **efficiently** model nonlinear dynamic systems with a moderate number of parameters.
- This work compares two classical architectures using an example MDOF nonlinear system to assess their potential for ANC in automotive applications, and as building blocks for PIML architectures.



Benchmark system

- A **linear system** (chassis) driven through a **nonlinear** element (suspension) was used to represent the idealised car.
- A **3-mode MDOF nonlinear system** was simulated [a], subject to a displacement input x(t) through a nonlinear Duffing spring, giving output displacement y(t).

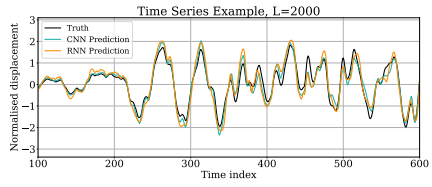
Physics models

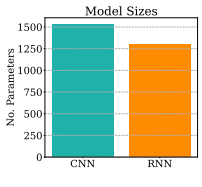
- In a road vehicle, vibration travels through the tyre, suspension, chassis, to the cabin, resulting in undesirable acoustic emissions. Direct cabin sound measurement is difficult, so wheel hub accelerations are used.
- Previous work by De Brett et al. [1] showed that the suspension introduces **complex physics** and **significant nonlinearity** into the transfer pathway. But multiple connection points to the chassis mean it **cannot be 'measured out'.**
- Both parameter-fitted physics and data-driven models were attempted, with Convolutional Neural Networks (CNNs) showing the most promise.

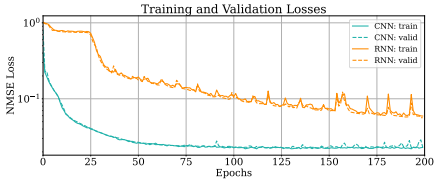
Data-driven models

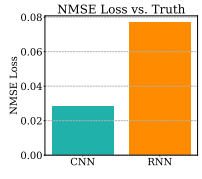
- Two standard **model architectures** with representative structures were trialled to assess their suitability for modelling nonlinear dynamic systems:
  - **RNN:** a Recursive Neural Network passes a hidden state as memory between timesteps, analogous to an Infinite Impulse Response (IIR) filter.
  - **CNN:** a Convolutional Neural Network optimises a basis of discrete convolution filters, analogous to a set of Finite Impulse Responses (FIR).
- For ANC, a small, **low-latency** yet **high accuracy** model is required, leading to a specific set of performance metrics (including the **coherence**).

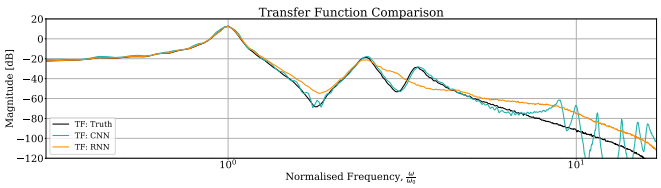
Performance

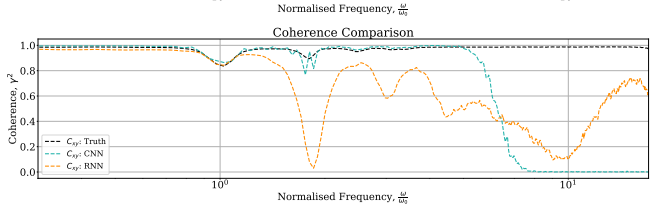












Conclusions

1. For representative model structures with a similar number of parameters, the **CNN** resulted in far **lower normalised loss** than the RNN.
2. The RNN struggled to model the **third mode** compared to the CNN, displaying far worse coherence across the simulated frequency range.
3. Crucially, a CNN can operate in **parallel**, resulting in a lower model latency than the sequential RNN – essential for ANC on embedded hardware.
4. However, both models have a **limited range** of operation. Therefore, inclusion of **physics-information** into the model architectures may aid performance where purely data-driven models show poor coherence.

Further work: PIML

- Physics informed machine learning [2] (PIML) is a growing field of study whereby physics information is incorporated into data-driven models in several ways:

Increasing strength

  - **'Physics-informed'** models use a physics term in their loss function.
  - **'Physics-guided'** models incorporate prior knowledge of the physical laws, for example the linearised governing equation.
  - **'Physics-encoded'** models have architectures tailored to the physics of the system to reproduce its known symmetries.
- Such models have potential in nonlinear systems, particularly if they can be leveraged to **separate** the nonlinear and linear behaviour of the system.
- For example, a model architecture could use a **known linear** system (the chassis and acoustics) whilst optimising for an **unknown nonlinearity** (the suspension coupling), reducing the model size and latency.

[a] Time series data was simulated using a Newmark-Beta scheme, generating N samples of length L subject to pulsed bandlimited white noise to provide N independent frames of data for model training and validation.

[1] M. De Brett, T. Butlin, L. Andrade, and O. M. Nielsen, 'Experimental investigation into the role of nonlinear suspension behaviour in limiting feedforward road noise cancellation', Journal of Sound and Vibration, Jan. 2022.

[2] A. Cicirello, 'Physics-Enhanced Machine Learning: a position paper for dynamical systems investigations', Jun. 08, 2024, arXiv:2405.05987. Accessed: May. 06, 2025. [Online]