A time series autoencoder for load identification via dimensionality reduction of sensor recordings

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The dimension of data acquired by sensor systems in civil engineering makes extremely difficult their use in raw forms.
Sensor data are usually shaped as **Multivariate Time Series** (MTS).

To manage sensor data, **synthetic features**, like peak spectral frequencies, are extracted.
AutoEncoders (AE) are special types of Neural Networks (NN) able to obtain a reduced data representation.

Advantages related to the use of AE for sensor data dimensionality reduction:

• **no feature engineering** is necessary;
• the obtained data representation can be used for **different tasks**;
• they provide the reduced representation that **best allows to reconstruct data a posteriori**.

From the reduced representation, it is possible to accomplish **regression tasks**. In this work, we tackle the issue of **load identification** in civil structures.
for any $i$ we sample $\alpha^i$ and $\phi^i$ from

\begin{align*}
\mathcal{U} (0.075, 1.025) \text{ kN/m} \\
\mathcal{U} (25, 325) \text{ Hz}
\end{align*}

where $\mathcal{U}$ indicates a uniform continuous probability density function.

\[ h^i_m = 0.5 m \alpha^i \sin \left( 2\pi \phi^i t \right) \]

Two-floors shear building model (undamped).

\[ V^i = \begin{bmatrix} v_1^i, v_2^i \end{bmatrix} \]

where $v_m^i$ collects the displacement recordings of the $m$-th floor of the $i$-th MTS.

\[ T = 5 \text{ s} \]
\[ \Delta t = 0.02 \text{ s} \]
\[ L = 250 \]

*from now on we omit the superscript

is it possible to identify the loading conditions by operating the regression of $\eta^i$ on $V^i$؟
Time Series Autoencoder (1D convolutional layers)

\[ N^{\text{out}} \]

(number of channels in output to the convolutional layer)

\[ N \]

(number of channels in input to the convolutional layer)

discrete convolution operation

\[ u_n (V, \Omega_n) = \sum_{b=1}^{N} \omega_n^b \ast v_b, \quad n = 1, \ldots, N^{\text{out}} \]
A Time Series Autoencoder (dimensionality reduction)

\[
V = [v_1, \ldots, v_N] \in \mathbb{R}^{L \times N} \xrightarrow{enc} z \in \mathbb{R}^P \xrightarrow{dec} U = [u_1, \ldots, u_N] \in \mathbb{R}^{L \times N}
\]

where in general \( P \ll (L \cdot M) = 250 \cdot 2 = 500 \)

encoder

stack of convolutional layers + inception modules [1]

decoder

dilated convolutions [2]

\[ u_r \in \mathbb{R}^Q \]

minimise \( c_r (\eta, u_r) \)

\[ c(V, U) \]

[minimise]


Time Series Autoencoder (inverse problem solution)

\[ V = [v_1, \ldots, v_N] \in \mathbb{R}^{L \times N} \]

\[ \text{enc} \rightarrow \quad z \in \mathbb{R}^p \]

\[ \text{dec} \rightarrow \quad U = [u_1, \ldots, u_N] \in \mathbb{R}^{L \times N} \]

Reduced representation (latent variables)

Minimise \( c(V, U) \)

Regression tool

\[ u_r \in \mathbb{R}^Q \]

Minimise \( c_r(\eta, u_r) \)
Numerical results: signal reconstruction

**Reconstructed signal**

\[ \times 10^{-5} \times 10^{-6} \]

\[ v_2, u_2 [m] \]

\[ t [s] \]

(a) \( \alpha^i = 702 \, \text{N}, \phi^i = 3.56 \, \text{Hz} \)

(b) \( \alpha^i = 4341 \, \text{N}, \phi^i = 9.45 \, \text{Hz} \)

**AE signal reconstruction when \( \phi^i \) is close to the structural frequencies \( f_{str} = [3.93, 10.3] \, \text{Hz} \)
reconstruction error computed for 512 \( \mathbf{v}^i \) unseen during the training of the AE according to the standardised \( L^2 \) error norm.

\[ \left\| \mathbf{u}_2 - \mathbf{v}_2 \right\|_2 / \sigma(\mathbf{v}_2) \]

highest error for \( \phi^i \) close to the structural frequencies.
reconstruction error computed for 512 $\mathbf{v}^i$ unseen during the training of the AE according to the standardised $L^\infty$ error norm.

highest error for $\phi^i$ close to the second structural frequency.
Numerical results: regression outcomes

Results obtained for $P = 4$.

Load identification is satisfactorily accomplished through the regression of $\alpha^i$ and $\phi^i$ on $z$. 
Thank you for your attention!

Essential Bibliography:


