Complexity analysis and machine learning for analysis of critical care data

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Predicting extubation failure using complexity measures

Motivation

- Extubating a patient on ventilator support too early or too late can lead to fatal outcomes
- Major post extubation complications reported between 25 and 50% cases(1; 2).
- Growing evidence that measures from complex dynamical systems can help predict extubation failure(2).

Question

- Are there any differences in complexity based measures between children who failed extubation and those who do not?
- Can these differences be used to predict extubation failure?

Method

- We start with heart rate and respiratory rate data from 6 hours before the extubation
- The standard deviation, Higuchi dimension and multiscale entropy of the data are calculated
- Heart and respiratory rate measures are known to be closely related to age(3).
- Differences are checked using a t-test and studied separately for younger and older children.

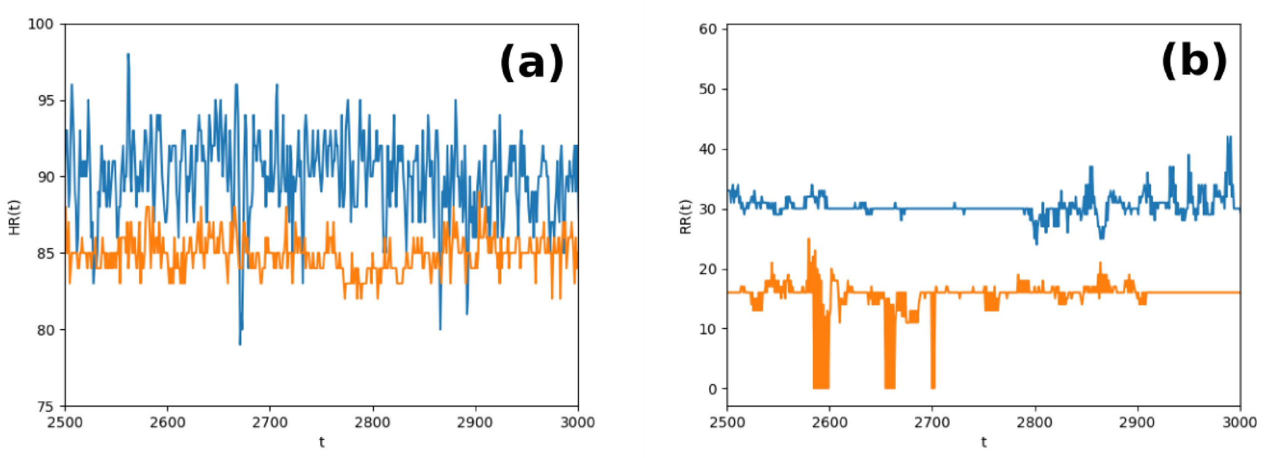

Figure 1: Sample time series of (a)heart rate and (b) respiratory rate from a patient who did not fail extubation (blue) and one who did (orange)

Heart rate

- No significant differences were found in the three quantifiers between the children who failed extubation and those who did not.
- Sample was then divided into categories according to median age.
- No significant differences were found even after, in either group.

Respiratory rate

- No significant differences was found between children who failed extubation and those who did not
- Sample was then divided into categories according to median age.
- No significant differences were found in younger children who failed extubation and did not.
- Significant differences were found between the two groups for standard deviation and multiscale entropy for older children.

Property	$\mu_F \pm SD$	$\mu_S \pm SD$	t-statistic	p-value
SD_Y	9.609 ± 3.724	8.525 ± 4.170	1.574	0.124
MSE_Y	1.125 ± 0.355	1.129 ± 0.337	0.057	0.955
HD_Y	1.850 ± 0.142	1.866 ± 0.116	-0.612	0.545
SD_O	4.888 ± 2.607	4.093 ± 2.163	2.212	0.030*
MSE_O	0.964 ± 0.390	0.835 ± 0.463	2.331	0.027*
HD_O	1.836 ± 0.150	1.846 ± 0.149	-0.501	0.617

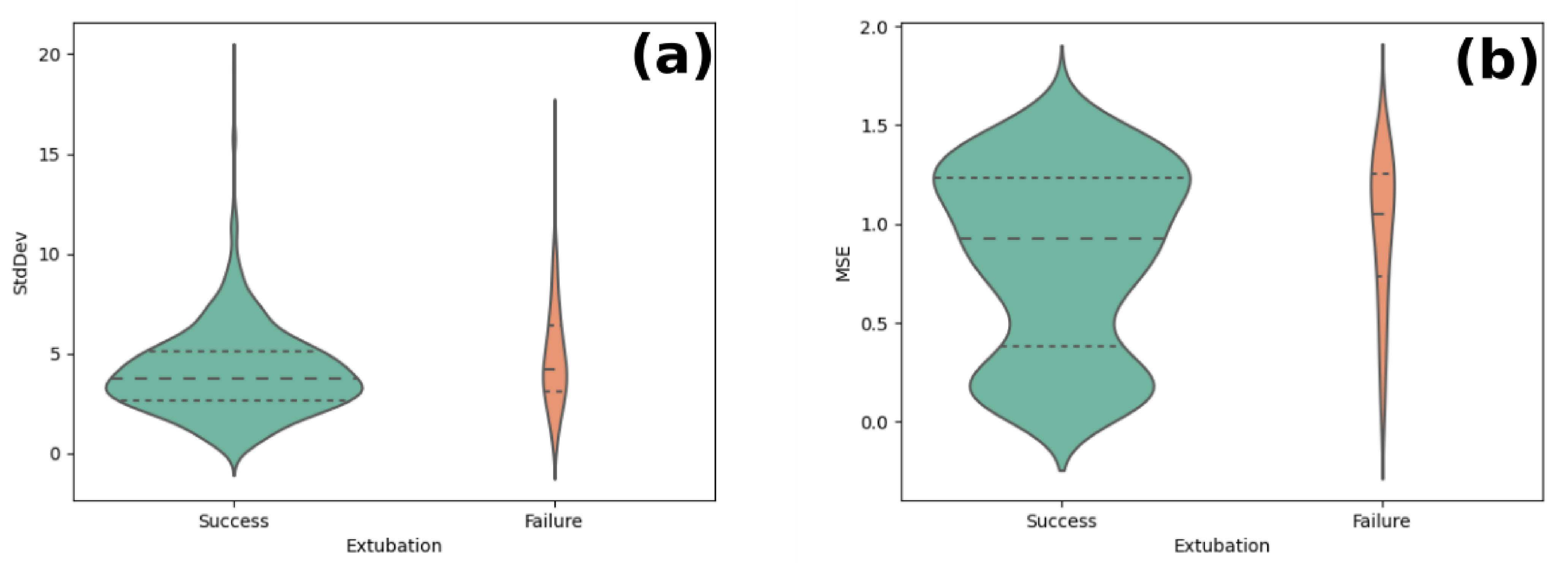

Figure 2: Differences in the distributions of (a) standard deviation and (b)multi-scale entropy between children who failed extubation (orange) and those who did not (green), in a sample of older children.

Conclusions and future directions

- Shows promise in the use of nonlinear time series measures to predict extubation failure, in limited cases.
- Need to replicate with a larger sample.
- Possible to use in combination with machine learning tools in order to achieve greater accuracy.

Predicting dynamical properties using echo state networks

Motivation

- Recurrent neural networks, such as echo state networks(ESN), have shown promise in predicting chaotic attractors upto 6 or 7 Lyapunov times (4; 5).
- But the algorithm can learn the attractor, or the "climate" of the system with comparative ease(6).

Question

- How well do echo state networks predict the attractor climate?
- How does the prediction accuracy change with data length and size of the hidden layer (reservoir size)?

Echo State Networks

- The echo state network consists of an input layer, a hidden reservoir layer and an output layer(4).
- The reservoir weights are chosen randomly and fixed throughout the training.
- n: time step, u(n): input state, x(n): reservoir state, y(n): output state, W: reservoir strength matrix, W^{in}: input weight matrix, W^{out} : output feedback matrix and f: sigmoid function, the state update equation of the reservoir is given as

$$\vec{x}(n+1) = f(\mathbf{W}\vec{x}(n) + \mathbf{W^{in}}\vec{u}(n+1) + \mathbf{W^{out}}\vec{y}(n))$$

- The extended system, $\vec{z}$ is the concatenation of the reservoir and input states, $\vec{z}(n) = [\vec{x}(n); \vec{u}(n)]$, whose state is given by

$$\vec{y}(n) = f(\mathbf{W^{out}}\vec{z}(n))$$

- Only the W^{out} is trained during the training phase, greatly reducing the computation time.

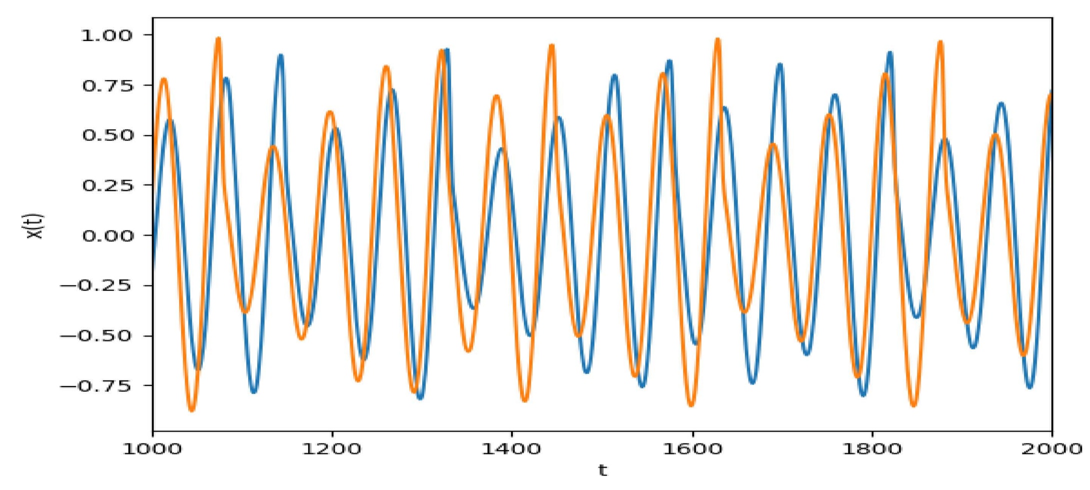

Figure 3: Comparison of the original time series from the Rössler (blue) and the prediction of the ESN(orange) using 500 data points and a reservoir size of 1000.

Method

- Start with time series from a dynamical system (we use the Rössler system)
- Calculate an attractor metric (in our case, the correlation dimension).
- Train ESN of reservoir size N with a time series of length L.
- Predict the future evolution using the ESN and calculate its correlation dimension.
- Vary N and L and repeat process

Results

- The fractal dimension did not show significant variation with N or L.
- The stability of the echo state network was poor, and the network was often found to be unstable.

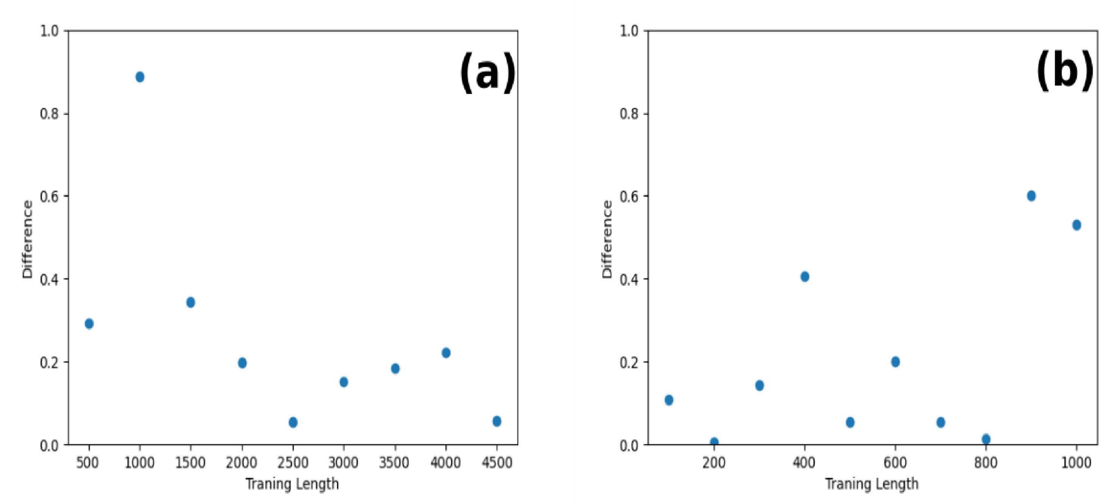

Figure 4: Variation of the correlation dimension from the original value varying (a) length of training data (b) size of the hidden layer (reservoir)

Conclusions and future directions

- Attractor properties of a short chaotic time-series can be calculated from ESN based predictions
- This could be in part because the original dynamics was noise free and low dimensional
- One could use these to interpolate through gaps, when conducting nonlinear analysis
- Useful when classifying short waveform time series in the ICU, using complexity based analysis.
- Need to improve ESN stability by fine tuning hyper parameters

Acknowledgements

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References

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