

Learning Beyond Simulated Physics

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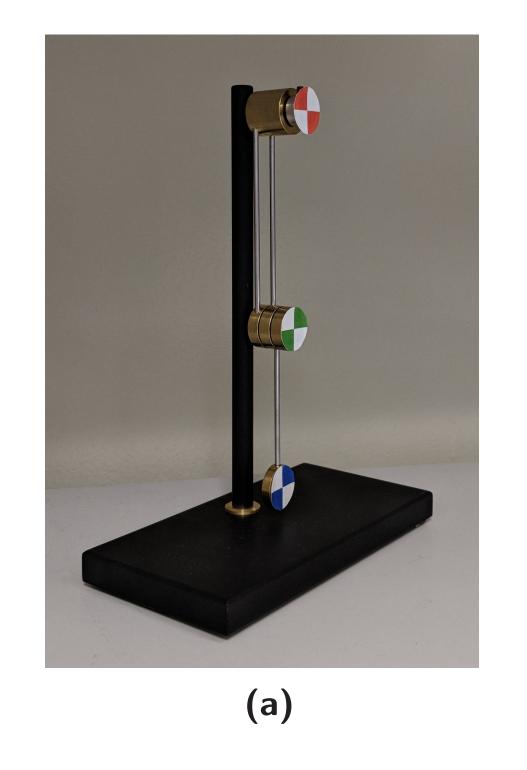


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Abstract

Most advancements in terms of time-series predictions of physical systems is based on simulated physics. Thus we are proposing a new dataset based on videos of a real-world, chaotic double pendulum. We show baseline performance using an LSTM model, demonstrating the possibility of training directly on a real physical system.

The Double Pendulum



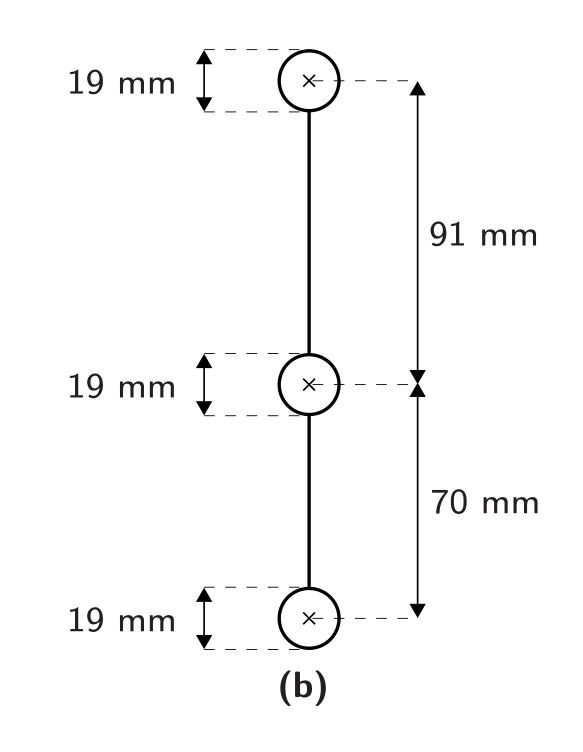


Figure 1: A picture 1a and the dimensions 1b of the double pendulum.

The double pendulum is a **chaotic**[3] mechanical device. Even though it can be simulated, we chose to use a real one to create the Double Pendulum Chaotic Dataset. The behavior of the pendulum is influenced by environmental noise, i.e. air motion, coupling with the table, imperfections of the device, etc.

Data Acquisition

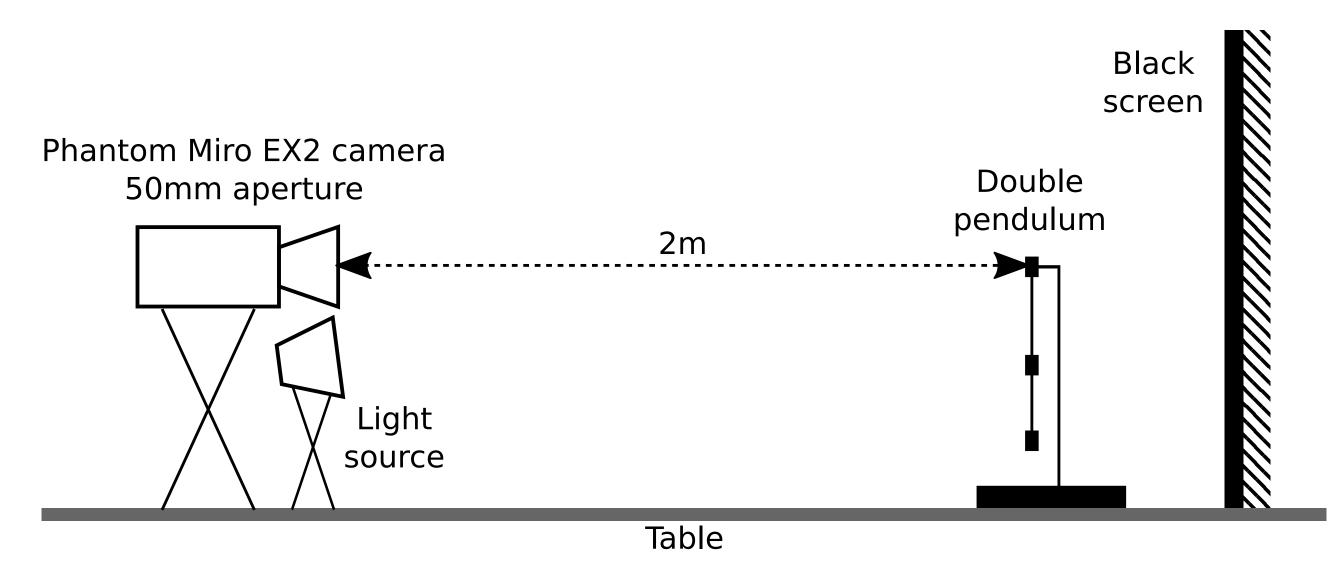


Figure 2: Camera set-up.

Camera settings	
Resolution Capture frame-rate Frame exposure time	480x480 pixels 400 Hz 90 μs
Data properties	
Sequence capture duration Number of frames per sequence Number of sequences	pprox 40 s $pprox$ 17500

Table 1: Summary of the video settings

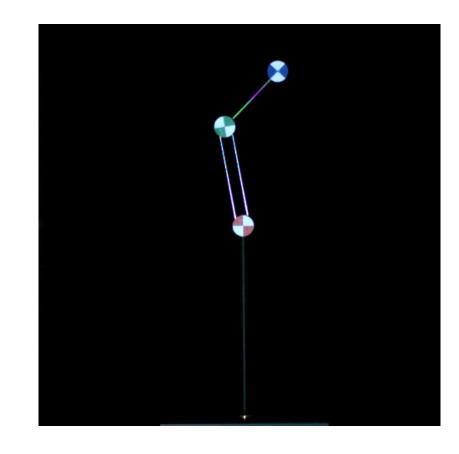


Figure 3: A video frame.

The Dataset

The dataset is available as:

- Full length, high quality videos
- Corresponding CSV files of the positions through time

And the ones above, precut as a train/test dataset, such that:

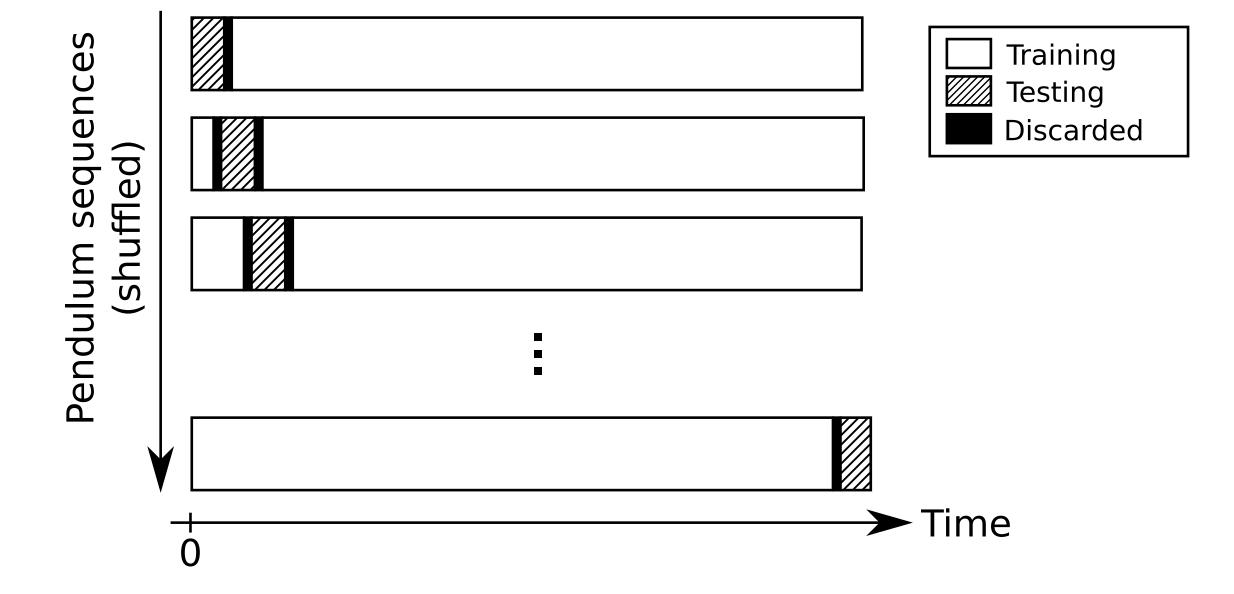


Figure 4: Split of the dataset (To scale).

Where the testing data is cut in sequences of 4 input frames and 200 prediction ground-truth frames.

ML baseline with LSTM

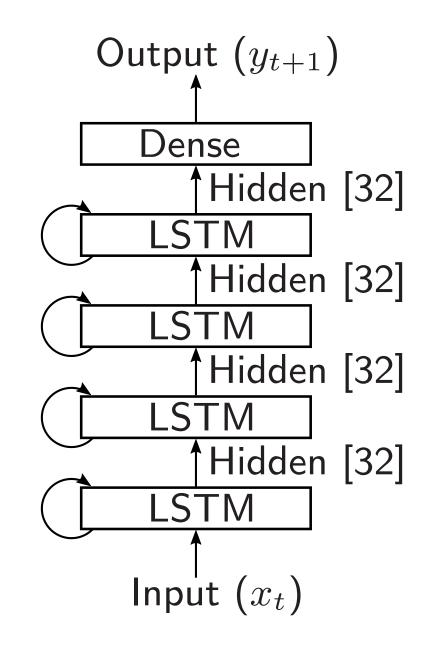


Figure 5: Diagram of the LSTM[1]-based recurrent neural network used. It takes one time-step as input and predicts the next one.

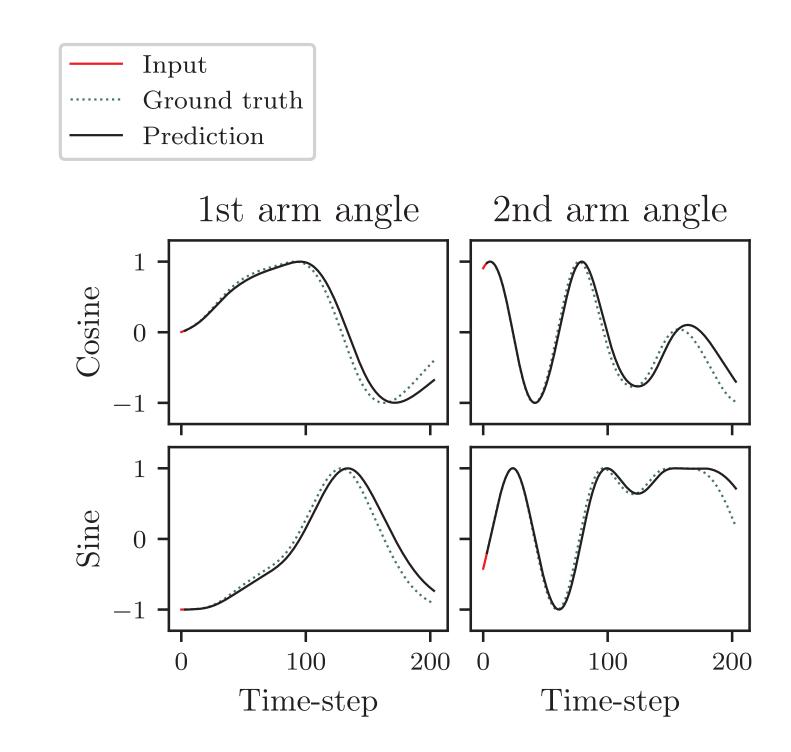
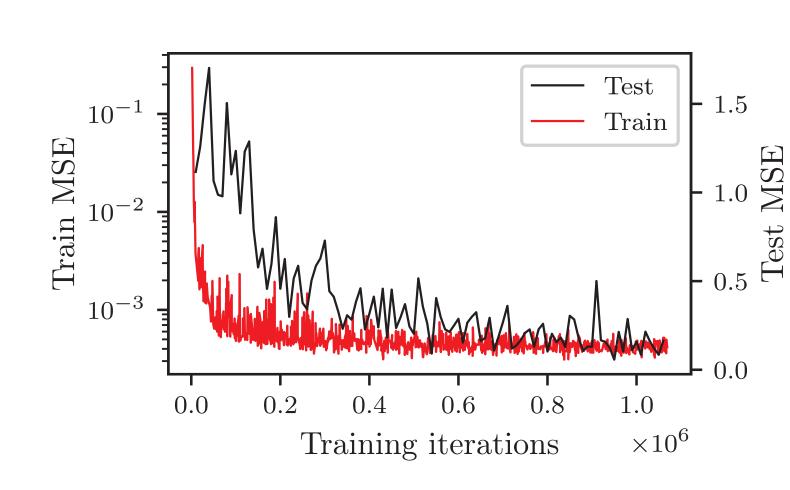


Figure 6: Example of a predicted sequence.

1st arm angle

SE(sine)

2nd arm angle



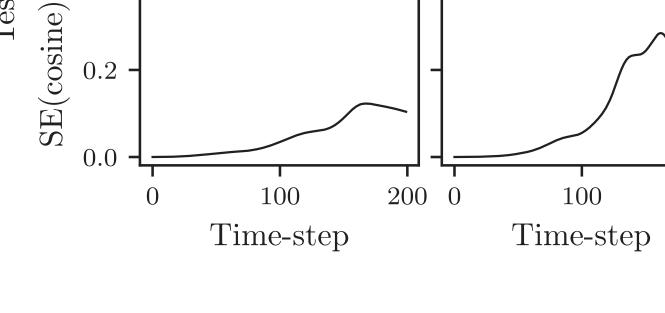


Figure 7: Training convergence, using Adam[2] as optimizer.

Figure 8: Square error per time-step, averaged over all the test samples. RMSE = 0.30

References

- [1] S. Hochreiter and J. Schmidhuber. Long short-term memory. 9:1735–80, 12 1997.
- [2] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014.
- [3] R. B. Levien and S. M. Tan. Double pendulum: An experiment in chaos. *American Journal of Physics*, 61(11):1038–1044, 1993.

The Double Pendulum Chaotic Dataset:

https://ibm.github.io/double-pendulum-chaotic-dataset/