Two-Legged Robot System Identification With Artificial Neural Networks

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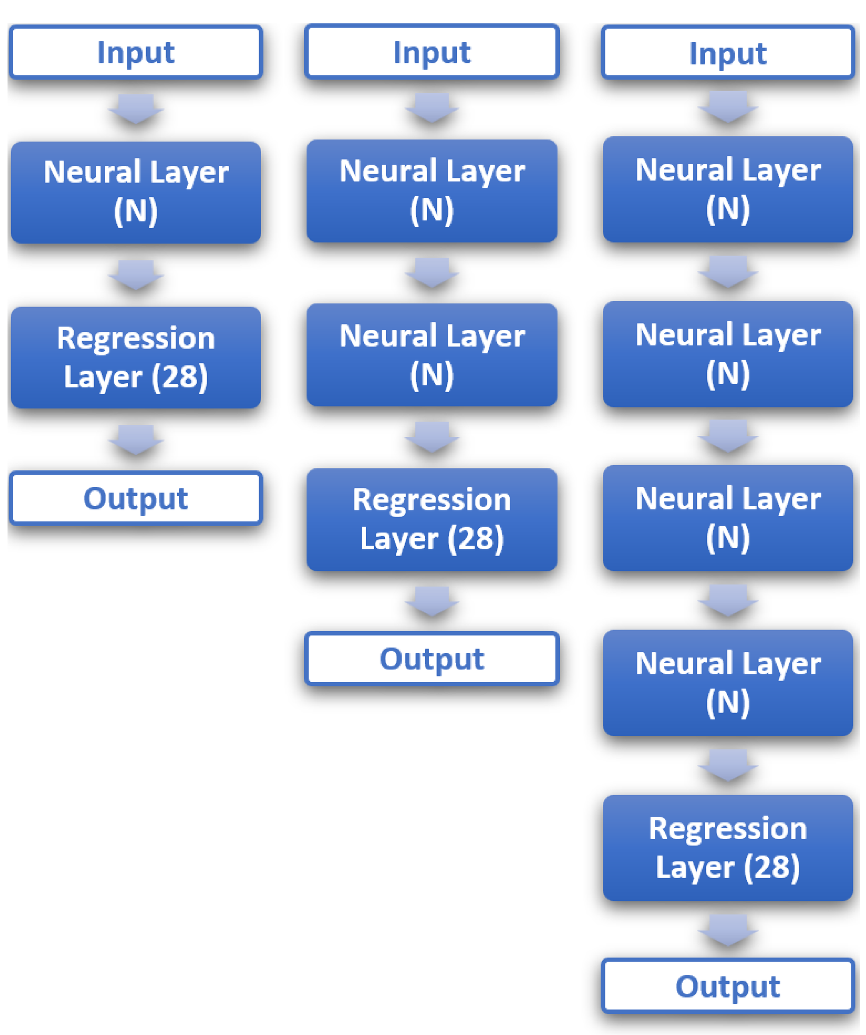
INTRODUCTION

- Two-Legged Robot System Identification is an important topic of research.
- The robot platforms have a dynamic structure with flight & contact phases.
- This hybrid dynamic structure and non-linear dynamics make it harder to calculate the system Jacobian needed for the adaptive control methods.
- Different neural networks are used in this study to make system identification.
- Supervised training is done with central pattern generator creating stable walking datasets, which are used by feedforward and recurrent networks.

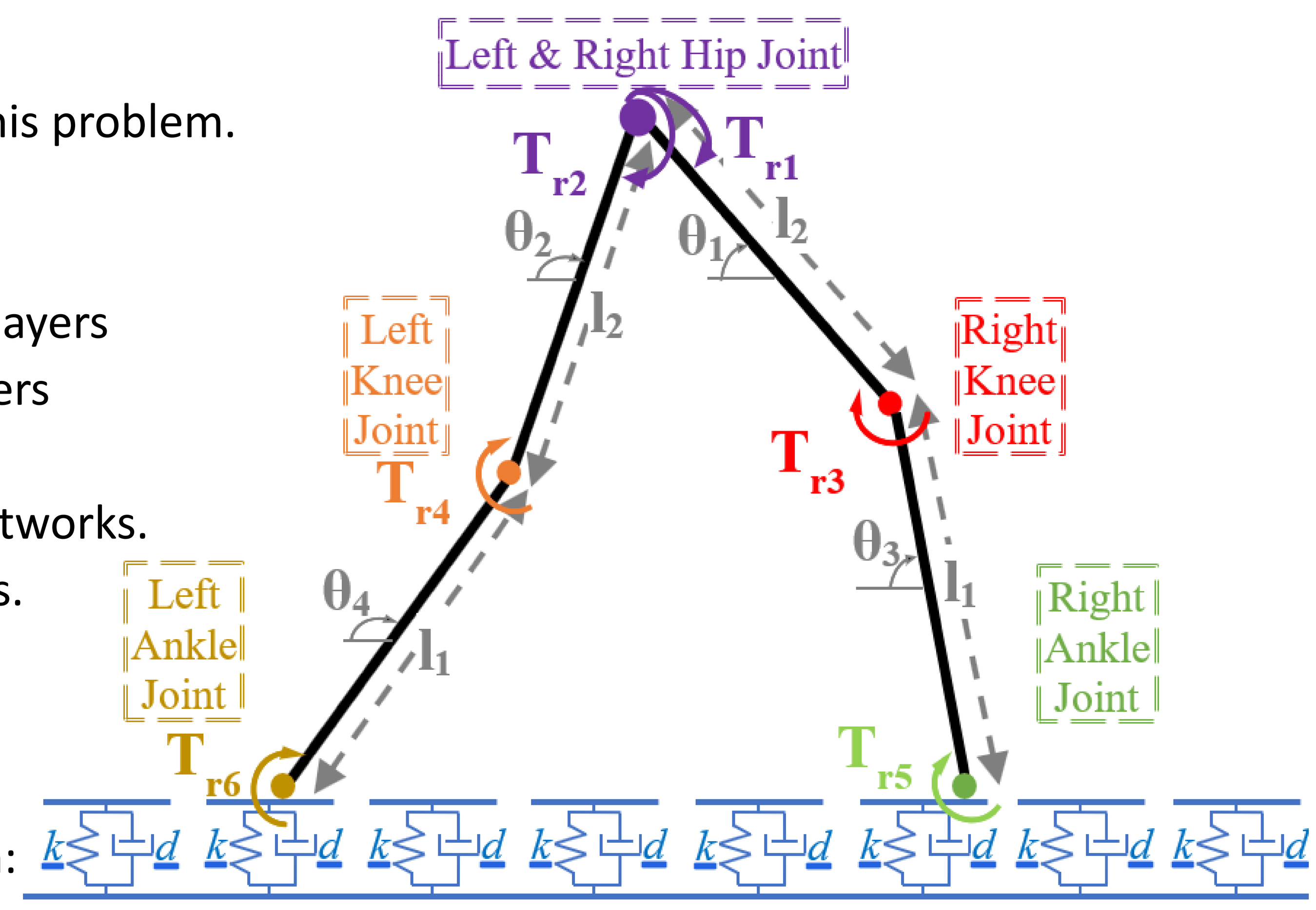
DATASET

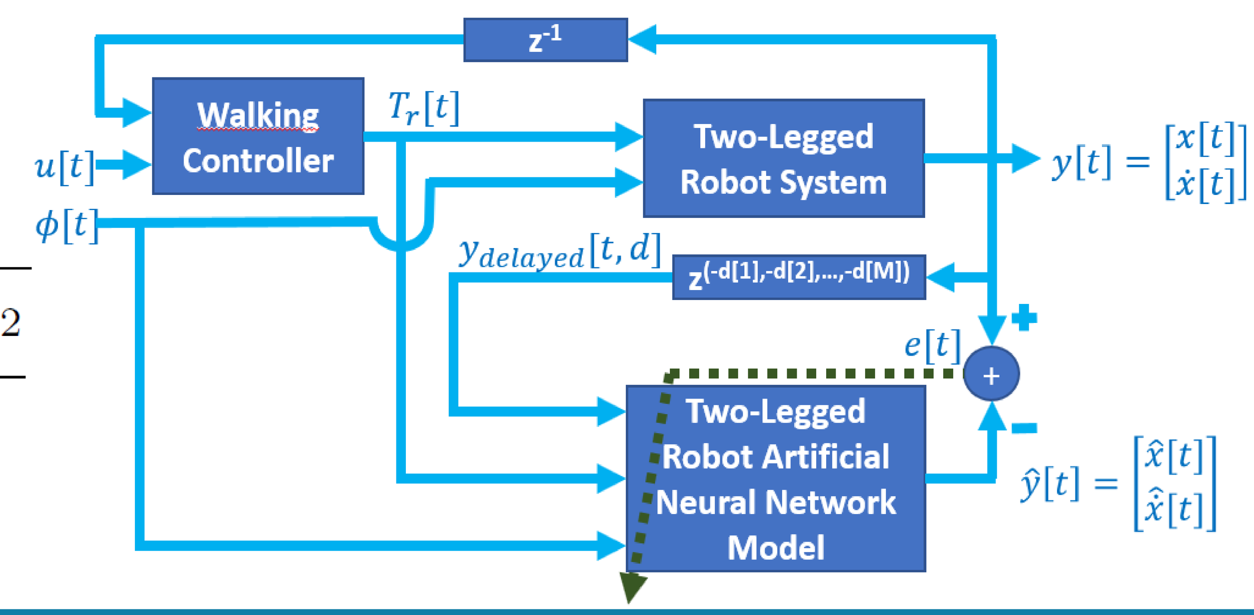
- Data is generated from a 2-legged robot system model with 4 parts & 6 joints.
- System models non-linear dynamics too, such as ground response and friction.
- Hybrid dynamic robot platform is combined with Central Pattern Generator:
  - → It consists of 6 Matsuoko oscillators with coupling.
  - → The samples are taken with 100 Hz frequency for a duration of 10 seconds.
  - → In total, 380 training, 189 verification and 141 test patterns are generated.

SYSTEM ARCHITECTURE



- Artificial Neural Networks (ANN) are proposed for solving this problem.
- Different types of neural networks are employed this work:
  - → Feedforward Neural Networks with different number of layers
  - → Recurrent Neural Networks with different number of layers
- 2, 3 and 5 layers-network formations are used for neural networks.
  - → All networks used linear & hyperbolic tangent activations.
- The networks are used to make the system identification.
- The serial-parallel architecture for the identification is given:





$$E = \sqrt{\sum_{t=1}^{N} \frac{(y[t] - \hat{y}[t])^2}{N}} = \sqrt{\sum_{t=1}^{N} \frac{(e[t])^2}{N}}$$

$$y_{delayed}[t, d] = \begin{bmatrix} y[t-d[1]] \\ y[t-d[2]] \\ \dots \\ y[t-d[M]] \end{bmatrix}, \quad d = [1, 2, \dots, M]$$

RESULTS

- Multiple tables are given as results for 2, 3 and 5-layer networks.
- Both recurrent and feedforward neural networks are compared:
  - → Recurrent networks are used with different neuron amounts.
  - → Feedforward networks are applied in this manner as well:
  - → In addition, different input delays are also applied to them.
- The best result is obtained by recurrent (LSTM) networks:
  - → The largest neuron amount and least number of layers is used.
  - → Reasons: Increased capability of network and less complexity.
  - → 1.77% test error is the best one, also for the training phases.

TABLO II: Single Hidden Layer Neural Networks

Number of Weights	HL Neuron Type	HL Neuron Number	Input Delay	System Characterization Error (RMSE) Training	Verification	Test
18628	LSTM	N=50	d=[1]	$1,61 \cdot 10^{-2}$	$1,99 \cdot 10^{-2}$	$2,38 \cdot 10^{-2}$
	FF (tanh)	N=291	d=[1]	$3,1 \cdot 10^{-2}$	$3,28 \cdot 10^{-2}$	$3,43 \cdot 10^{-2}$
	FF (tanh)	N=203	d=[1,2]	$2,88 \cdot 10^{-2}$	$3,07 \cdot 10^{-2}$	$3,23 \cdot 10^{-2}$
	FF (tanh)	N=155	d=[1,2,3]	$2,84 \cdot 10^{-2}$	$3,05 \cdot 10^{-2}$	$3,26 \cdot 10^{-2}$
	FF (tanh)	N=126	d=[1,2,3,4]	$2,83 \cdot 10^{-2}$	$3,02 \cdot 10^{-2}$	$3,17 \cdot 10^{-2}$
57228	LSTM	N=100	d=[1]	$1,17 \cdot 10^{-2}$	$1,62 \cdot 10^{-2}$	$1,97 \cdot 10^{-2}$
	FF (tanh)	N=894	d=[1]	$3,3 \cdot 10^{-2}$	$3,44 \cdot 10^{-2}$	$3,57 \cdot 10^{-2}$
	FF (tanh)	N=622	d=[1,2]	$2,89 \cdot 10^{-2}$	$3,09 \cdot 10^{-2}$	$3,22 \cdot 10^{-2}$
	FF (tanh)	N=477	d=[1,2,3]	$2,84 \cdot 10^{-2}$	$3 \cdot 10^{-2}$	$3,2 \cdot 10^{-2}$
	FF (tanh)	N=387	d=[1,2,3,4]	$2,78 \cdot 10^{-2}$	$2,98 \cdot 10^{-2}$	$3,16 \cdot 10^{-2}$
194428	LSTM	N=200	d=[1]	$\mathbf{0,81 \cdot 10^{-2}}$	$\mathbf{1,3 \cdot 10^{-2}}$	$\mathbf{1,77 \cdot 10^{-2}}$
	FF (tanh)	N=3038	d=[1]	$3,37 \cdot 10^{-2}$	$3,55 \cdot 10^{-2}$	$3,64 \cdot 10^{-2}$
	FF (tanh)	N=2114	d=[1,2]	$3,06 \cdot 10^{-2}$	$3,24 \cdot 10^{-2}$	$3,36 \cdot 10^{-2}$
	FF (tanh)	N=1620	d=[1,2,3]	$3,02 \cdot 10^{-2}$	$3,14 \cdot 10^{-2}$	$3,34 \cdot 10^{-2}$
	FF (tanh)	N=1314	d=[1,2,3,4]	$2,85 \cdot 10^{-2}$	$3,06 \cdot 10^{-2}$	$3,16 \cdot 10^{-2}$

TABLO III: Double Hidden Layer Neural Networks

Number of Weights	HL Neuron Type	HL Neuron Number	Input Delay	System Characterization Error (RMSE) Training	Verification	Test
38828	LSTM	N=50	d=[1]	$1,29 \cdot 10^{-2}$	$1,78 \cdot 10^{-2}$	$2,16 \cdot 10^{-2}$
	FF (tanh)	N=168	d=[1]	$2,28 \cdot 10^{-2}$	$2,57 \cdot 10^{-2}$	$2,8 \cdot 10^{-2}$
	FF (tanh)	N=156	d=[1,2]	$2,12 \cdot 10^{-2}$	$2,4 \cdot 10^{-2}$	$2,59 \cdot 10^{-2}$
	FF (tanh)	N=146	d=[1,2,3]	$2,08 \cdot 10^{-2}$	$2,35 \cdot 10^{-2}$	$2,55 \cdot 10^{-2}$
	FF (tanh)	N=137	d=[1,2,3,4]	$2,07 \cdot 10^{-2}$	$2,31 \cdot 10^{-2}$	$2,49 \cdot 10^{-2}$
137628	LSTM	N=100	d=[1]	$\mathbf{0,89 \cdot 10^{-2}}$	$\mathbf{1,44 \cdot 10^{-2}}$	$\mathbf{2,03 \cdot 10^{-2}}$
	FF (tanh)	N=340	d=[1]	$2,14 \cdot 10^{-2}$	$2,57 \cdot 10^{-2}$	$2,68 \cdot 10^{-2}$
	FF (tanh)	N=328	d=[1,2]	$1,98 \cdot 10^{-2}$	$2,2 \cdot 10^{-2}$	$2,47 \cdot 10^{-2}$
	FF (tanh)	N=316	d=[1,2,3]	$2,01 \cdot 10^{-2}$	$2,38 \cdot 10^{-2}$	$2,52 \cdot 10^{-2}$
	FF (tanh)	N=304	d=[1,2,3,4]	$1,96 \cdot 10^{-2}$	$2,34 \cdot 10^{-2}$	$2,42 \cdot 10^{-2}$

TABLO IV: Four Hidden Layer Neural Networks

Number of Weights	HL Neuron Type	HL Neuron Number	Input Delay	System Characterization Error (RMSE) Training	Verification	Test
79228	LSTM	N=50	d=[1]	$\mathbf{1,16 \cdot 10^{-2}}$	$\mathbf{1,72 \cdot 10^{-2}}$	$\mathbf{2,33 \cdot 10^{-2}}$
	FF (tanh)	N=152	d=[1]	$1,95 \cdot 10^{-2}$	$2,36 \cdot 10^{-2}$	$2,92 \cdot 10^{-2}$
	FF (tanh)	N=148	d=[1,2]	$1,78 \cdot 10^{-2}$	$2,28 \cdot 10^{-2}$	$2,42 \cdot 10^{-2}$
	FF (tanh)	N=144	d=[1,2,3]	$1,82 \cdot 10^{-2}$	$2,3 \cdot 10^{-2}$	$2,44 \cdot 10^{-2}$
	FF (tanh)	N=140	d=[1,2,3,4]	$1,86 \cdot 10^{-2}$	$2,3 \cdot 10^{-2}$	$2,54 \cdot 10^{-2}$

CONCLUSION & FUTURE WORK

- In this work, system identification is done by different neural networks using a synthetic dataset generated with CPG.
- In comparison, recurrent neural network is the best choice, while delayed inputs can improve feedforward ones better.
- High number of neurons with less number of layers seems as the best strategy to follow in this type of problems.
  - → As a future work, using other initialization, optimizer and regularization techniques can improve the performance.

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IMPORTANT REFERENCES

[1] B. Çatalbaş, "Recurrent neural network learning with an application to the control of legged locomotion," Master's thesis, Bilkent University, 2015.

[2] S. Hochreiter, and J. Schmidhuber, "Long short-term memory.", *Neural computation*, vol. 9, no. 8, pp. 1735-1780, 1997.

[3] A. V. D. Schaft and H. Schumaher, *An introduction to hybrid dynamical systems.* Springer London, 2000, vol. 251.

[4] W. T. Miller, P. J. Werbos, and R. S. Sutton, *Neural networks for control*. MIT press, 1995.

[5] V. Kasparian and C. Batur, "Model reference based neural network adaptive controller," *ISA transactions*, vol. 37, no. 1, pp. 21-39, 1998.