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DATA-DRIVEN TUNING OF LSTM CONTROLLERS FOR SYSTEMS WITH NONLINEARITIES

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Abstract. *This paper presents a controller architecture composed only of a long short-term memory (LSTM) which is a kind of recurrent neural network and proposes a data-driven tuning method for the controller. The feature of the presented control system configuration and tuning method is to compensate for various types of plant nonlinearities in a simplified and integrated manner only with input and output data and with no information of plant models. Considering the system configuration, virtual reference feedback tuning (VRFT) is used as an appropriate data-driven controller tuning method. The effectiveness of the presented control system configuration and tuning method is demonstrated with some simulation results.*
Keywords: Data-driven controller tuning, Nonlinearity, Neural network, LSTM, VRFT

1. **Introduction.** Data-driven controller tuning [1, 2] has recently received significant attention from practical aspects because it uses only control input and output data and does not require information of plant mathematical models. As such tuning methods, virtual reference feedback tuning (VRFT) and fictitious reference iterative tuning (FRIT) have been proposed and developed for not only linear systems but also systems with nonlinearities such as dead zones, hysteresis, saturation, and backlash [3, 4, 5, 6]. The key idea to deal with these nonlinearities in the previous works is to use a model of an inverse nonlinearity as a nonlinear compensator so as to neutralize the nonlinearity. However, to apply these methods, we have to know which type of nonlinearity exists in the plant in advance although we do not have to know the detailed model parameters.

One intuitive solution to this difficulty is to use a nonlinear compensator composed of a neural network (NN) which can express various nonlinearities in a common architecture. In this case, however, the overall controller typically must consist of a linear controller and a nonlinear compensator which are used to compensate for a plant dynamics and a nonlinearity, respectively. As a result, the control system configuration and the tuning process are slightly complicated.

On the other hand, a long short-term memory (LSTM) which is a kind of recurrent NN has been found extremely successful in many fields such as speech recognition and machine translation [7]. One of the reasons is that the LSTM can handle long-term dependencies more easily than the simple recurrent NN architectures. Thus, it is expected that the LSTM is also effective for control-related fields in which dynamical systems are basically dealt with. In fact, the LSTM has recently been applied to system identification [8], parameter estimation [9], decision making [10], and controller parameter tuning [11], while the LSTM is hardly used as a controller itself. To the best of our knowledge, there is no application where LSTM-based controllers are tuned especially in the framework of data-driven tuning.

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In this paper, we present an LSTM-based controller and its tuning method in the framework of VRFT. The academic and practical contributions of this paper are summarized as follows.

- We propose a controller composed only of an LSTM and show that it provides a good control performance for systems with nonlinearities.
- The proposed LSTM-based controller can be easily implemented and effectively tuned by means of recently developed deep learning tools.

The rest of this paper is organized as follows. In Section 2, we first state typical control system configurations for feedback control and nonlinear compensation and then present an LSTM-based controller which can deal with various nonlinearities in a simplified and integrated manner. Section 3 presents a tuning method for the LSTM-based controller in the framework of VRFT after explaining the standard VRFT method and its modified version for nonlinear compensation. In Section 4, we confirm the effectiveness of the presented method through some simulation results. Finally, the conclusion is provided in Section 5.

2. **Control System Configuration.** We consider a control system configuration as shown in Figure 1 where $u(k)$, $y(k)$, $r(k)$, and $e(k)$ denote the control input, the control output, the reference signal, and the control error, respectively. We suppose that the plant is composed of a finite dimensional linear part and a nonlinearity such as a dead zone and a hysteresis element. When the plant shown in Figure 1 contains a nonlinearity, we may not obtain a good control performance even though only a linear controller such as a proportional-integral-derivative (PID) controller is implemented and sufficiently tuned via VRFT.

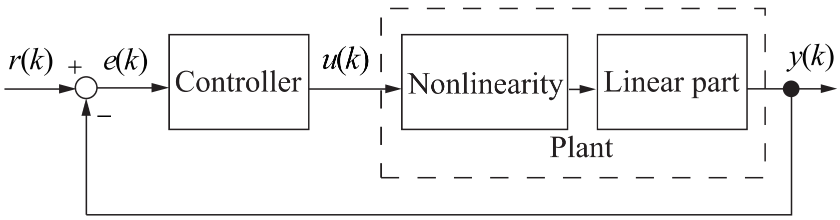

Figure 1. System configuration with a controller

As stated in Introduction, one solution to this difficulty is to introduce a nonlinear compensator as shown in Figure 2 [3, 4, 5, 6], and when it is composed of an NN, it is intuitively expected to be more effective for various nonlinearities. A typical NN has a multilayer feedforward architecture as shown in Figure 3, and each node corresponds to an activation function for which we will use a rectified linear unit (ReLU) in the first and second layers and a logistic sigmoid function in the third layer in the simulation section.

In the above case, however, parameters of a linear controller and an NN compensator have to be tuned alternatively. To simplify the controller architecture and tuning process, we again consider the system configuration in Figure 1 and use only an LSTM as a controller. The multilayer structure of the LSTM is the same as that of the feedforward

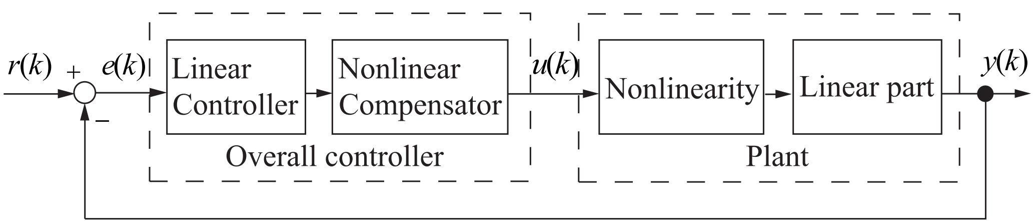

Figure 2. System configuration with a controller and a compensator

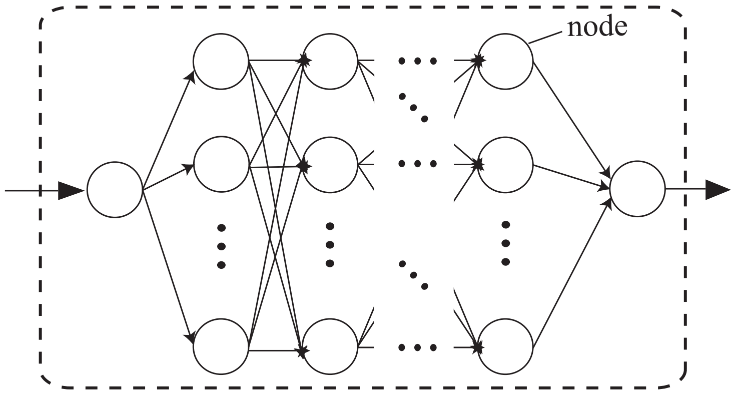

FIGURE 3. Structure of multilayer NNs

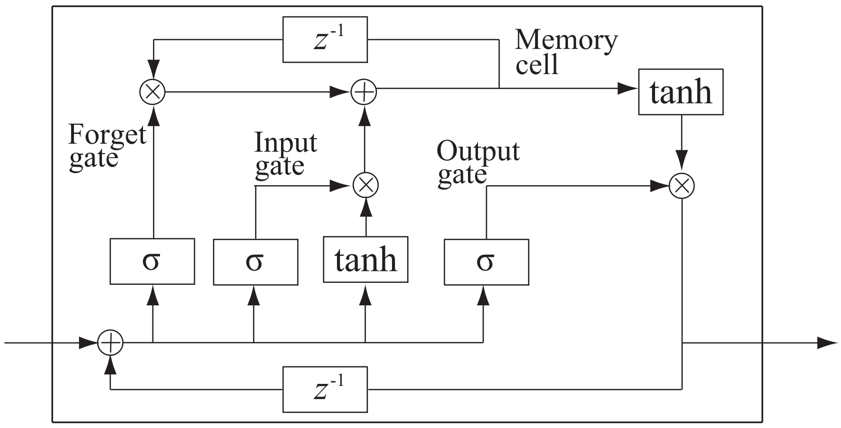

FIGURE 4. LSTM node

NN in Figure 3, while each node of the LSTM is more complicated as shown in Figure 4 [7]. Each LSTM node consists of 4 elements which are a memory cell, an input gate, an outupt gate, and a forget gate. The input gate, the output gate, and the memory cell are controlled through the gate values limited to the range $[0, 1]$. In Figure 4, tanh and σ denote a hyperbolic tangent and a logistic sigmoid function, respectively, which are activation functions.

It should be noted that LSTMs as well as NNs can be easily implemented by recently developed NN-related tools, i.e., deep learning frameworks such as Chainer [12].

3. **Controller Tuning.** In this section, we present a VRFT-based controller tuning method for systems with various nonlinearities after explaining the standard VRFT and its modified version for nonlinearities.

3.1. **Standard VRFT for a linear controller.** We first consider the control system configuration in Figure 1 with a linear controller $C(z;\boldsymbol{\theta})$ where $\boldsymbol{\theta}$ is a parameter vector. In the standard VRFT, we find $\boldsymbol{\theta}$ so that the performance index

$$J_1(\boldsymbol{\theta}) = \sum_{k=1}^{n} \left(u_0(k) - C(z;\boldsymbol{\theta})\bar{e}(k)\right)^2$$

is minimized after obtaining initial input and output data $\{u_0(k),\, y_0(k)\}$ from an initial closed-loop experiment with a given reference signal $r(k)$. Here, $\bar{e}(k)$ is $\bar{e}(k) = \bar{r}(k) - y_0(k)$; $\bar{r}(k)$ is a virtual reference signal satisfying $y_0(k) = M(z)\bar{r}(k)$; and $M(z)$ is a reference model.

3.2. **VRFT for a linear controller and an NN compensator.** To improve a performance for nonlinear compensation, we next consider the control system configuration in Figure 2 with a linear controller and a nonlinear compensator composed of a feedforward NN. In this case, the performance index to be minimized is expressed by

$$J_2(\boldsymbol{\theta}, \boldsymbol{w}_{\mathrm{N}}) = \sum_{k=1}^{n} \left(u_0(k) - \bar{u}(k; \boldsymbol{\theta}, \boldsymbol{w}_{\mathrm{N}})\right)^2, \tag{1}$$

where $\boldsymbol{w}_{\mathrm{N}}$ is the parameter vector including NN weights and biases, and $\bar{u}(k; \boldsymbol{\theta}, \boldsymbol{w}_{\mathrm{N}})$ is the output of the NN when $\bar{e}(k)$ is given to the overall controller. As mentioned in the previous section, we have to tune the two parameters $\boldsymbol{\theta}$ and $\boldsymbol{w}_{\mathrm{N}}$ alternatively. To do this, it is recommended that $\boldsymbol{\theta}$ be first tuned without the NN compensator, $\boldsymbol{w}_{\mathrm{N}}$ be next tuned with the fixed $\boldsymbol{\theta}$, and finally $\boldsymbol{\theta}$ be tuned with the fixed $\boldsymbol{w}_{\mathrm{N}}$. This alternative tuning will be carried out in the simulation as demonstrated later.

3.3. **VRFT for an LSTM controller.** To simplify the tuning process shown in the previous subsection, we then consider the control system configuration in Figure 1 with an LSTM controller.

Since the evaluation of the linear controller is removed from (1), the performance index in this framework is expressed by

$$J_3(\boldsymbol{w}_{\mathrm{L}}) = \sum_{k=1}^{n} \left(u_0(k) - \bar{u}(k; \boldsymbol{w}_{\mathrm{L}})\right)^2,$$

where $\bar{u}(k; \boldsymbol{w}_{\mathrm{L}})$ is the output of the LSTM with the parameter vector $\boldsymbol{w}_{\mathrm{L}}$.

4. **Simulation Results.** In this section, we verify the effectiveness of the presented method in Subsection 3.3 denoted by "VRFT-LSTM" for systems with some nonlinearities through simulation. For comparison, we carry out the standard VRFT in Section 3.1 denoted by "VRFT" and the modified version in Section 3.2 denoted by "VRFT-NN". In this simulation, the algorithm programmed in Python 3.5.4 and Chainer 6.4.0 [12] was run on a computer with 4.20 GHz Intel Core i7-7700K CPU and 32.0 GB RAM.

We consider a plant with the discretized linear part of $G(s) = 1/(0.5s + 1)$ and the hysteresis nonlinearity [4]

$$\xi(k) = \frac{1 - \xi(k-1)}{1 + e^{12-20u(k)}} + \frac{\xi(k-1)}{1 + e^{-20u(k)}}$$

and use a PID controller as a linear controller in the methods of VRFT and VRFT-NN. We set the initial PI gains as $\boldsymbol{\theta}_0 = [K_{\mathrm{P}}, K_{\mathrm{I}}]^T = [1, 0.1]^T$ (i.e., the D gain K_{D} is 0), the sampling time as 10 ms, and the reference signal as a signal consisting of multiple sinusoidal signals with various amplitudes in $[0.05, 0.95]$, as shown in Figure 5 (left).

Under the above settings, we first carry out a closed-loop simulation to obtain initial input and output data as shown in Figure 6.

Next we let the reference model be a discretized model of $M(s) = (0.1s+1)^2/(0.5s+1)^2$ and use the LSTM controller and the NN compensator which have a common structure of 3 hidden layers and 15 nodes in each hidden layer. Here, we set this structure by trial and error, in which we found that the resulting control performance cannot be improved so significantly even though the numbers of layers and nodes in the above settings are increased. We set initial weights in the LSTM controller and the NN compensator by randomly sampling from the normal distribution with zero mean and unit variance and set initial biases to 0.

We set the maximum number of iterations in the learning method as 500 for both the LSTM controller and the NN compensator. This number of iterations was determined by trial and error so that the issues of over-fitting were avoided in the resulting control performance. The optimization algorithm "Adam" implemented in Chainer is used for

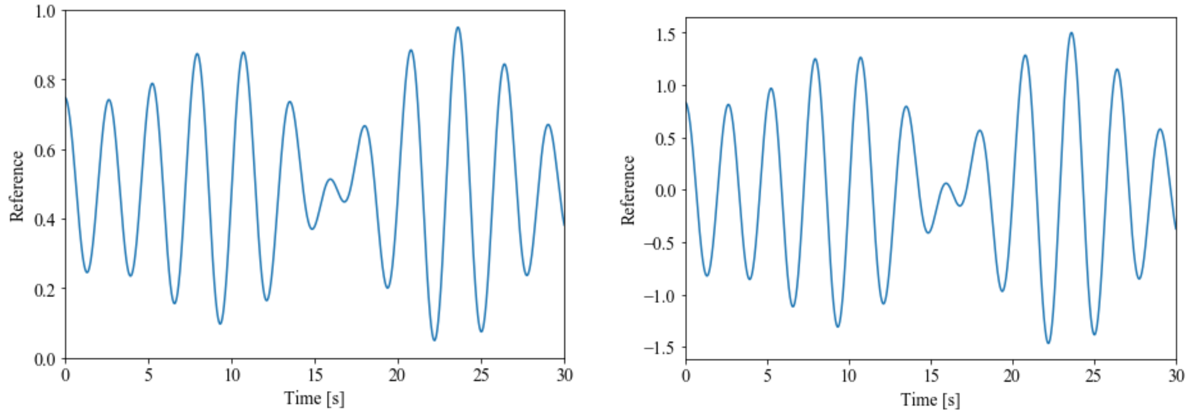

FIGURE 5. Reference signals for systems with the hysteresis nonlinearity (left) and the other nonlinearities (right)

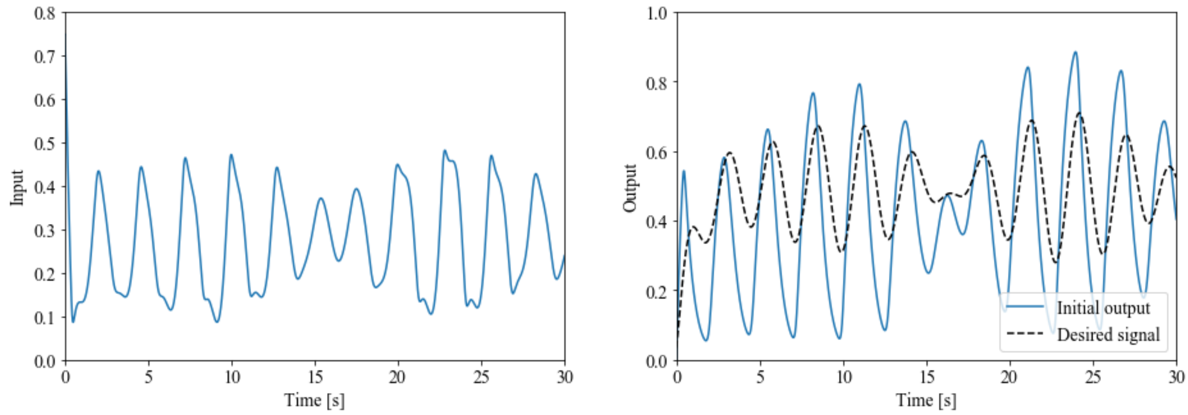

FIGURE 6. Initial control input and output

the learning method, and the other parameters for the learning method are basically set to default values recommended in Chainer. To tune PID gains in VRFT and VRFT-NN, the optimization command "fmin" is used with the default setting parameters.

Under the abovementioned settings, we obtained the three controllers. The computation times for VRFT, VRFT-NN, and VRFT-LSTM are 40 s, 98 s, and 2022 s, respectively. We then carried out closed-loop simulations with these controllers. The control inputs and outputs obtained from the simulations are shown in Figure 7. We see from Figure 7 that VRFT-LSTM provides a better tracking performance than VRFT and VRFT-NN. It should be noted that the presented method VRFT-LSTM is simply computed and implemented and outperforms other data-driven methods, while such long computation time is generally acceptable for off-line control design.

To verify the effectiveness of the presented method in more detail, we conduct simulations for systems with other nonlinearities as follows: the dead zone

$$\xi(k) = \begin{cases} u(k) + 0.35 & u(k) < -0.35 \\ 0 & -0.35 \leq u(k) \leq 0.35 \\ u(k) - 0.35 & u(k) > 0.35, \end{cases}$$

the cubic function

$$\xi(k) = 3u(k)^3,$$

and the square root

$$\xi(k) = \begin{cases} -2\sqrt{-u(k)} & u(k) < 0 \\ 0 & u(k) = 0 \\ 2\sqrt{u(k)} & u(k) > 0. \end{cases}$$

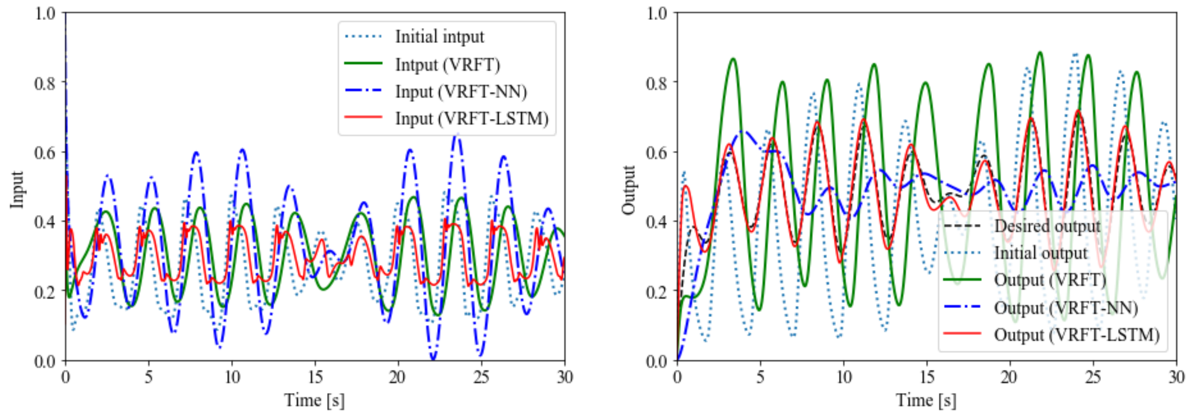

FIGURE 7. Resulting control input and output

We set a reference signal so that the center of the range becomes 0 as shown in Figure 5 (right). We evaluate the control performance by using

$$J^* = \sum_{k=1}^{n} (y(k) - M(z)r(k))^2.$$

The control performances of the systems with nonlinearities are shown in Table 1. We see from the table that the presented VRFT-LSTM provides smaller performance index values than the initial simulation, VRFT, and VRFT-NN for all the cases. In particular, it can be seen that VRFT-LSTM significantly outperforms VRFT and VRFT-NN for systems with hysteresis. Noting that hysteresis is a dynamical nonlinearity and the others are static ones, we see this result is reasonable since the LSTM is originally effective for long-term dependencies as well as nonlinearities. Therefore, this apparently confirms that the presented control system configuration and the tuning method are effective for systems with nonlinearities.

TABLE 1. Control performance evaluated by J^*

	Init. sim.	VRFT	VRFT-NN	VRFT-LSTM
Hysteresis	106.8065	126.9252	42.5066	3.7864
Dead zone	130.2501	25.1727	11.9293	11.8949
Cubic func.	211.9739	51.6738	14.8398	13.0259
Square root	686.6549	41.6043	20.1088	14.4337

5. **Conclusion.** We have presented a control system configuration with an LSTM controller and its tuning method and also have shown the effectiveness of the presented method through simulation results. The controller in the presented configuration is composed only of an LSTM, which leads to high compensation capability for various nonlinearities as well as a simple and practical model free controller tuning method by combining the VRFT. To improve the presented method, computation time reduction and a sophisticated setting method for the numbers of layers and nodes in the LSTM controller should be considered as future research directions.

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