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ONLINE DATA-DRIVEN CONTROL USING AN ECHO STATE NETWORK

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Abstract. *In contrast to model-based control, data-driven control does not require a modeling process. Due to its simplicity, it has been attracting attention in recent years, and the related research is conducted to expand its range of application and improve its performance. This paper presents a controller architecture composed of only an echo state network which is a kind of neural network in the framework of reservoir computing and proposes an online data-driven controller tuning method. The feature of the proposed method is to realize fast and online controller tuning for systems with nonlinear elements. The effectiveness of the proposed method was verified by comparing it with a conventional method through simulations and an actual experiment.*
Keywords: Data-driven control, Nonlinearity, Neural network, ESN, VRFT

1. **Introduction.** While classical model-based control has developed as a reliable method in the control field, data-driven control, which does not require models, has recently attracted attention due to its simplicity [1]. Virtual reference feedback tuning (VRFT) [4] is a data-driven controller tuning method for tuning controller parameters such as proportional-integral-derivative (PID) gains. VRFT has become popular and is known to be useful because it is based on only a set of input and output data and does not require a plant model and any iterative experiments. Taking advantage of these features, various extensions of VRFT and its similar methods have been attempted, such as robust PID control [2] and look-up-table-based control [3].

Although VRFT has been developed basically for linear systems, it is extended to systems with nonlinearities by introducing a controller composed of a long short-term memory (LSTM) which is a kind of recurrent neural network (RNN) [5]. The LSTM-based VRFT method proposed in [5] is effective for systems with various nonlinear elements such as a dead zone and hysteresis. However, it has the disadvantage that it tends to take much time to adjust the controller parameters.

On the other hand, since VRFT and its similar method, fictitious reference iterative tuning (FRIT), are usually carried out offline, they cannot respond to changes in plant characteristics due to operational situations. To overcome this drawback, online FRIT has been proposed by combining with the recursive least-squares (RLS) [6]. However, the

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proposed online FRIT [6] is intended for linear controllers such as a PID controller, and therefore, is not suitable for systems with nonlinear elements.

In this paper, we first present controller architecture based on an echo state network (ESN) [7], which is a kind of RNN and can approximate dynamic nonlinear systems in a relatively short computation time. Then, we propose an online controller tuning method by applying the RLS algorithm in the framework of VRFT, unlike FRIT of [6]. Consequently, the proposed online data-driven control method can respond to changes of systems with nonlinear elements. As similar works to the presented method, the ESN-based fuzzy learning control [8] and the online control with two kinds of ESNs for training and control [9] have been recently proposed. It should be noted that, however, these methods have more complicated control architecture and are therefore more difficult to be implemented than the presented method. The effectiveness of the proposed method is confirmed by comparing it with the previous method [6] through some simulations and an actual experiment of a system with hysteresis.

The rest of this paper is organized as follows. Section 2 proposes the architecture and algorithm of the online ESN-based VRFT, and Sections 3 and 4 show some numerical and experimental results, respectively. Finally, we conclude the paper in Section 5.

2. Online ESN-Based VRFT.

We consider the closed-loop system configuration as shown in Figure 1. The plant consists of a single-input and single-output discrete-time linear system $G(z)$ and a nonlinearity $\mathcal{N}$, and the controller $C(z,\boldsymbol{\theta})$ is tuned with respect to the controller parameter $\boldsymbol{\theta}$ such as PID gains of a PID controller. The signals $u(k)$, $y(k)$, $r(k)$, and $e(k)$ denote the control input, the control output, the reference signal, and the control error, respectively.

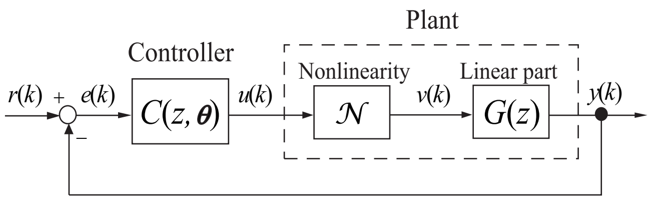

FIGURE 1. System configuration

In a typical offline VRFT, we first obtain a set of initial input and output data denoted by $u_0(k)$ and $y_0(k)$ from an initial closed-loop experiment, and next find $\boldsymbol{\theta}^*$ by minimizing the performance index $J_0(\boldsymbol{\theta}) = \sum_{k=1}^{n}(u_0(k) - C(z,\boldsymbol{\theta})\bar{e}(k))^2$, where $\bar{e}(k) = \bar{r}(k) - y_0(k)$ and $\bar{r}(k)$ is a virtual reference signal satisfying $y_0(k) = M(z)\bar{r}(k)$ with the reference model $M(z)$. As a result, an appropriate controller parameter $\boldsymbol{\theta}^*$ is obtained for any reference signal $r(k)$. See more details in [4].

The differences between the proposed method and the typical VRFT are to utilize an ESN as a controller and to tune the controller parameter online as shown in the following subsections.

2.1. Architecture of ESN-based controller.

The ESN is a special RNN in which only the weights in the output layer are updated while the weights in the other layers, i.e., the input and hidden layers, are randomly given and fixed. This structure enables the hidden layers to work as a reservoir of nonlinear characteristics and the learning time of the ESN to be much shorter than the other RNNs [7].

As a controller to be tuned online, we employ the ESN represented by the following equations:

$$x_i(k+1) = \phi_i\left(\sum_{j=1}^{N} A_{ij}x_j(k) + be(k)\right), \tag{1}$$

$$u(k) = \sum_{j=1}^{N} c_j x_j(k) + de(k), \tag{2}$$

where

$$\phi_i(\zeta) = \begin{cases} \zeta & \text{for } i = 1, \ldots, N_p \\ \tanh(\zeta) & \text{for } i = N_p + 1, \ldots, N, \end{cases} \tag{3}$$

$$\boldsymbol{A} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & & & \\ \vdots & & \bar{\boldsymbol{A}} & \\ 0 & & & \end{pmatrix}. \tag{4}$$

The architecture of the ESN is shown in Figure 2. Here, $\boldsymbol{A} \in \mathbb{R}^{N \times N}$ and $b \in \mathbb{R}$ are the weights of the hidden layer and the input layer, respectively, and $x_i(k) \in \mathbb{R}$ ($i = 1, 2, \ldots, N$) are the state variables of the i-th unit of the ESN at time k. In addition, $\phi_i : \mathbb{R} \to \mathbb{R}$ represents an activation function, and N_p determines the ratios of linear and nonlinear activation functions. Since the output of the ESN is linear with respect to the weights $\boldsymbol{w} := [c_1, \ldots, c_N, d]^T$, they can be updated by the least-squares method, which allows for a short learning time [7]. For the stability of the ESN, the matrix $\boldsymbol{A}$ is usually set so that its spectral radius $\rho(\boldsymbol{A})$ is less than 1. However, because we aim at designing a tracking control system, we set $\boldsymbol{A}$ with the structure shown in (4) and $\rho\left(\bar{\boldsymbol{A}}\right) < 1$.

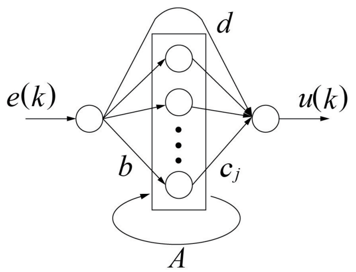

Figure 2. ESN architecture

2.2. **Online data-driven controller tuning algorithm.** According to the same manner as in [6], we modify the performance index $J_0(\boldsymbol{\theta})$ in the offline VRFT and derive the following performance index such that the RLS method can be applied:

$$J_k(\hat{\boldsymbol{w}}) = \sum_{i=1}^{k} \lambda^{k-i} \left(u(i) - \hat{\boldsymbol{w}}^T \boldsymbol{\xi}(i)\right)^2, \tag{5}$$

where $\hat{\boldsymbol{w}}(k)$ is a tentative parameter of the ESN controller, $\lambda > 0$ is a forgetting factor, and

$$\boldsymbol{\xi}(k) = [x_1(k), x_2(k), \ldots, x_N(k), s(k)]^T, \tag{6}$$

$$s(k) = M(z)^{-1} y(k) - y(k). \tag{7}$$

The RLS calculation for minimizing the performance index (5) is described as follows:

$$\boldsymbol{h}(k) = \frac{\boldsymbol{P}(k-1)\boldsymbol{\xi}(k)}{\lambda + \boldsymbol{\xi}(k)^T \boldsymbol{P}(k-1)\boldsymbol{\xi}(k)}, \tag{8}$$

$$\boldsymbol{P}(k) = \frac{\boldsymbol{P}(k-1) - \boldsymbol{h}(k)\left(\boldsymbol{\xi}(k)^T \boldsymbol{P}(k-1)\right)}{\lambda}, \tag{9}$$

$$\hat{\boldsymbol{w}}(k) = \hat{\boldsymbol{w}}(k-1) + \boldsymbol{h}(k)\left(u(k) - \boldsymbol{\xi}(k)^T \hat{\boldsymbol{w}}(k-1)\right), \tag{10}$$

$$\boldsymbol{P}(0) = \hat{\gamma}\boldsymbol{I}, \tag{11}$$

where $\hat{\gamma}$ is a parameter for an initial correlation matrix $\boldsymbol{P}(0)$. According to the RLS algorithm, the parameter $\hat{\boldsymbol{w}}(k)$ is updated at each sampling time. However, in the early stages of the algorithm or when the plant changes abruptly, the large change of this parameter may result in deterioration of the control performance, or even instability of the closed-loop system in the worst case. Therefore, in order to suppress the change of the controller parameter, we update $\boldsymbol{w}(k)$ to be implemented by using the following low pass filter:

$$\boldsymbol{w}(k) = (1-\alpha)\boldsymbol{w}(k-1) + \alpha\hat{\boldsymbol{w}}(k-1), \tag{12}$$

where $0 < \alpha < 1$ is a parameter of the filter. The proposed online data-driven controller tuning algorithm is summarized in Algorithm 1, and the block diagram of the algorithm is shown in Figure 3. As can be seen from the closed-loop structure in Figure 3, the ESN can potentially compensate for the nonlinearity of the plant in the VRFT framework and can respond to plant variation by updating its own weights at each time.

Algorithm 1: Online VRFT-ESN

Step 1. Initialization
  Set the initial weights $\hat{\boldsymbol{w}}(0) = \boldsymbol{w}(0)$ in the output layer randomly and set $M(z)$, γ, λ, and α.
Repeat Steps 2-4 for $k = 1, 2, \ldots$.
Step 2. Signal calculation
  Calculate $\boldsymbol{\xi}(k)$ according to (6) and (7).
Step 3. RLS algorithm
  Obtain $\hat{\boldsymbol{w}}(k)$ by computing (8)-(10).
Step 4. Implementation
  Update $\boldsymbol{w}(k)$ according to (12) and implement it in the ESN-based controller.

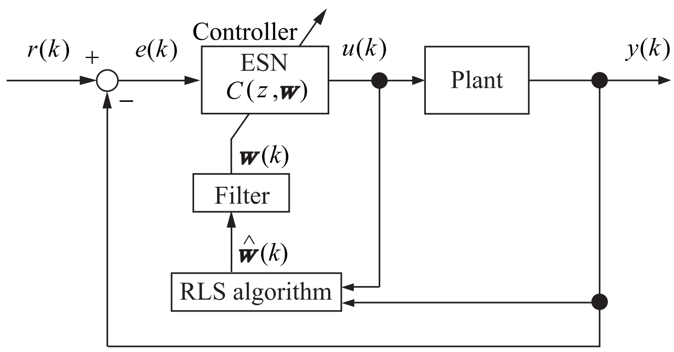

FIGURE 3. Block diagram of the online VRFT-ESN

3. **Simulation.** The proposed online data-driven control method denoted by VRFT-ESN is applied to plants with nonlinearities and changes while comparing with the conventional method denoted by FRIT-PID proposed in [6]. Let the linear part $G(z)$ be a discretized system of $G(s) = 1/(Ts+1)$ with sampling time of 10 ms and the time constant T be changed as follows:

$$G(s) = \begin{cases} 1/(s+1) & \text{for 0-58 s} \\ 1/(0.5s+1) & \text{for 58-118 s} \\ 1/(0.3s+1) & \text{for 118-180 s.} \end{cases} \tag{13}$$

As a nonlinearity $\mathcal{N}$, we consider a dead zone, hysteresis which is presented in [10], and a square root as shown below:

$$v(k) = D(u(k)) = \begin{cases} u(k) + 0.7 & \text{if } u(k) < -0.7 \\ 0 & \text{if } -0.7 \leq u(k) \leq 0.7 \\ u(k) - 0.7 & \text{if } u(k) > 0.7, \end{cases} \tag{14}$$

$$v(k) = H(v(k-1), u(k)) = \frac{-v(k-1) - 4}{1 + e^{0.01 - u(k)}} + \frac{v(k-1) + 5}{1 + e^{-0.01 - u(k)}} - 5, \tag{15}$$

$$v(k) = S(u(k)) = \begin{cases} -1.5\sqrt{-u(k)} & \text{if } u(k) < 0 \\ 1.5\sqrt{u(k)} & \text{if } u(k) \geq 0 \end{cases} \tag{16}$$

where $v(k)$ is the output of the nonlinearities. We set the reference signal $r(k)$ and the reference model $M(z)$ as a square wave and a discretized system of $M(s) = (0.1s + 1)/(0.5s + 1)$, respectively. We also set $N = 50$, $N_p = 25$, $\lambda = 0.999$, and $\alpha = 0.1$. Moreover, for a fair comparison, we set $\boldsymbol{\theta}(0) = [1, 0, 0]^T$ and $\boldsymbol{w}(0) = [0, 0, \ldots, 0, 1]^T$ so that the initial outputs of the two systems are the same. The simulations were run in Python 3.7.0 on a 3.60GHz Core i7-9700K CPU with 32GB of memory.

Table 1 shows the root mean squared errors (RMSEs) between the target output and the resulting outputs of the plants with the nonlinearities. We see from the table that in all cases, the RMSEs of VRFT-ESN are smaller than those of FRIT-PID, and therefore, the control outputs of VRFT-ESN follow the target outputs with higher accuracy than those of FRIT-PID.

TABLE 1. RMSE of VRFT-ESN and FRIT-PID

	VRFT-ESN	FRIT-PID
Dead zone	0.0192	0.1092
Square root	0.0123	0.0152
Hysteresis	0.0119	0.0143

As an example of the output transition, the case with the dead zone is shown in Figure 4. To see the tracking performance in more detail, Figure 5 shows the RMSEs every 2 seconds before the reference signal switches. It can be seen from Figures 4 and 5 that the control outputs deviate from the target output when the load is applied, but then that of VRFT-ESN follows the target output more quickly than that of FRIT-PID. This means that the proposed method, i.e., VRFT-ESN, works effectively for changes as well as nonlinearities in plants.

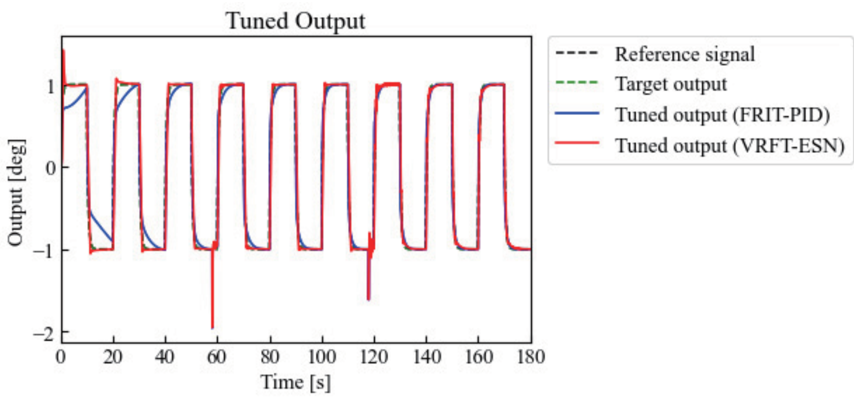

FIGURE 4. Control outputs in the case of the dead zone nonlinearity

4. **Experiment.** To validate the effectiveness of the proposed method through an actual system with a nonlinearity, we use the shape memory alloy (SMA) actuator system shown in Figure 6. It is known that SMA actuators exhibit inherent hysteresis characteristics.

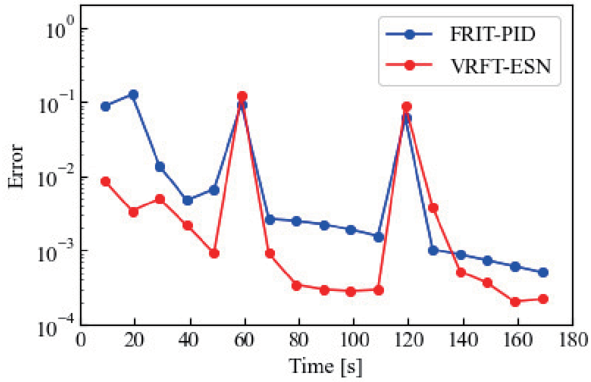

FIGURE 5. RMSE transition

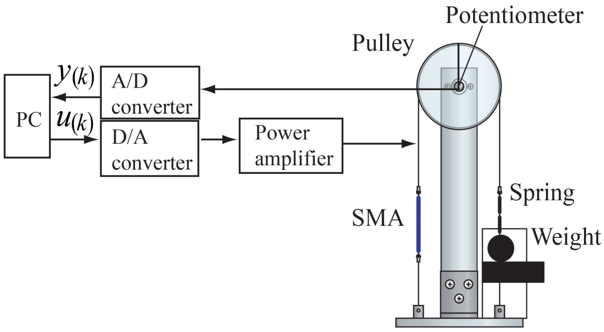

FIGURE 6. SMA actuator system

The input is the voltage of 0 to 5 V given to the SMA actuator, while the output is the rotation angle of the pulley caused by the expansion and contraction of the SMA actuator.

As in the simulation, we apply the proposed method, i.e., VRFT-ESN and the conventional method [6], i.e., FRIT-PID, to this system. We set the reference signal $r(k)$ and the reference model $M(z)$ as a trapezoidal wave and a discretized system of $M(s) = (1.5s + 1)/(1.6s + 1)$ with sampling time of 60 ms, respectively. We also set $N = 100$, $N_p = 50$, $\lambda = 0.9995$, and $\alpha = 0.00005$. Moreover, for a fair comparison, we set $\boldsymbol{\theta}(0) = [25, 0, 0]^T$ and $\boldsymbol{w}(0) = [0, 0, \ldots, 0, 25]^T$ so that the initial outputs of the two systems are the same. To evaluate the adaptability to plant changes, the SMA actuator is loaded with a weight after 350 seconds.

The resulting control output is shown in Figure 7. When the load weight was applied at the time of 350 seconds, the control outputs of the two methods deviated from the target output once, but then followed the target output, which indicates that they control the

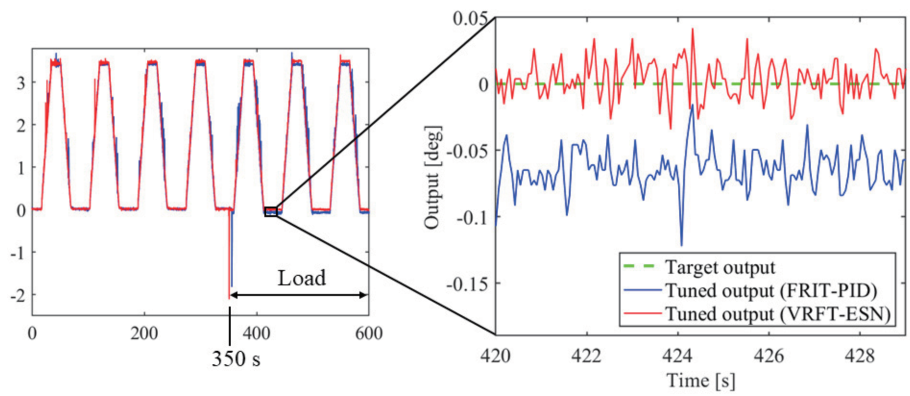

FIGURE 7. Resulting control output

plant change adaptively. It can also be seen from the figure that the control output of VRFT-ESN follows the target output more accurately than that of FRIT-PID [6]. The RMSEs between the control output and the target output were 0.0035 for VRFT-ESN and 0.0108 for FRIT-PID. This experimental result confirms the effectiveness of the proposed method.

5. **Conclusion.** In this paper, we have proposed an online data-driven control method using an ESN controller, and have verified its effectiveness through simulation and experimental results. We have confirmed that the proposed method is effective for plants with nonlinearities and can cope with changes in plant characteristics such as sudden loading. As future work, we seek a sophisticated way for the parameter selection and apply the proposed method to real-world control systems.

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