ISA Transactions 52 (2013) 752–758

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

Research Article

Improved single neuron controller for multivariable stochastic systems with non-Gaussianities and unmodeled dynamics

Jianhua Zhang [a,*], Man Jiang [b], Mifeng Ren [b], Guolian Hou [b], Jinliang Xu [c]

[a] State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing 102206, PR China
[b] School of Control and Computer Engineering, North China Electric Power University, Beijing 102206, PR China
[c] The Beijing Key Laboratory of New and Renewable Energy, North China Electric Power University, Beijing 102206, PR China

ARTICLE INFO

Article history:
Received 8 April 2013
Received in revised form
27 June 2013
Accepted 4 July 2013
Available online 30 July 2013
This aritcle was recommended for publication by Jeff pieper

Keywords:
Multivariable systems
Non-Gaussian noise
Improved neuron controller
(h,ϕ)-entropy
Sliding window

ABSTRACT

In this paper, a new adaptive control approach is presented for multivariate nonlinear non-Gaussian systems with unknown models. A more general and systematic statistical measure, called (h,ϕ)-entropy, is adopted here to characterize the uncertainty of the considered systems. By using the “sliding window” technique, the non-parameter estimate of the (h,ϕ)-entropy is formulated. Then, the improved neuron based controllers are developed for multivariate nonlinear non-Gaussian systems by minimizing the entropies of the tracking errors in closed loops. The condition to guarantee the strictly decreasing entropy of tracking error is presented. Moreover, the convergence in the mean-square sense has been analyzed for all the weights in the neural controllers. Finally, the comparative simulation results are presented to show that the performance of the proposed algorithm is superior to that of PID control strategy.

1. Introduction

Most practical industrial processes are inevitably subjected to random disturbances, which make the system extremely difficult to operate in an expected state. Research on general stochastic systems has been one of the hot-spot fields for several decades. Among the existed results, the noises are usually supposed to obey Gaussian distribution and most of the control strategies have been focused on the effective control of the mean and variance of the stochastic systems.

Neural networks (NNs) have attracted much attention for their potential to address a number of difficult problems in modeling, especially for stochastic systems with unknown nonlinear dynamics [1–7]. Some neural network based adaptive control algorithms have been presented for stochastic systems with Gaussian noises. In [5], the problem of robust stabilization was investigated for strict-feedback stochastic nonlinear time-delay systems via adaptive neural network approach. By using a NN to model the unknown packaged functions, a novel adaptive neural law was obtained by constructing a novel Lyapunov–Krasovskii function and backstepping in [6]. The single neuron adaptive control strategies were also proposed using mean squared error criterion [8–11].

The randomness in practical systems probably obeys non-Gaussian distribution, so the expectation and variance are no longer sufficient to characterize the statistical property of the stochastic systems. Thus, control methods in [5–6,8–11] may not achieve better control performance for the stochastic systems with non-Gaussian noises. Fortunately, stochastic distribution control (SDC) strategy has been proposed to deal with non-Gaussian systems since 1996, and there are some relative results (see [12–20]).

One kind of model based stochastic distribution controller is designed so that the shape of the probability density function (PDF) of the system output follows a target distribution. B-spline was used to approximate the measured output PDF, and the shape of the system output PDF can be controlled by manipulating the weights of the B-spline expansion (see e.g. [12–14]). Some other neural networks were also adopted to approximate the measured output PDF in [15–19]. A multi-layer perceptron (MLP) and a radial basis function (RBF) neural network were, respectively, applied to approximate the output PDFs of non-Gaussian stochastic distribution systems (SDSs) [15,16]. It is noted that the weights vector in the above mentioned neural networks dose not have apparent physical meaning. In addition, the size of neural networks may be very large if the distribution area of the output is wide or the output PDF shape is complicated.

To solve the above problems, another kind of model-based stochastic distribution controller was developed, where the entropy of the output (or tracking error) rather than the PDF

* Corresponding author. Tel.: +86 13811625884.
E-mail addresses: zjh@ncepu.edu.cn, zjhncepu@163.com (J. Zhang).

0019-0578/$ - see front matter © 2013 ISA. Published by Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.isatra.2013.07.002

shape of the system output was considered. The minimum entropy control laws were usually investigated by using state-space model or input–output ARMAX model [17–19]. The model parameters and the noises were bounded stochastic distribution with known PDFs in state space model [17]. In [18,19], the stochastic noises were bounded with known PDF in the pseudo ARMAX model with fixed parameters.

For some practical industrial processes with non-Gaussian noises, it is difficult to establish models, so it is hardly possible to use the above model-based SDC approaches for these processes. This calls for the model free stochastic distribution control strategy. Neural networks were used to both model and control nonlinear non-Gaussian systems, respectively, in [20]. A neural PID controller was proposed to control nonlinear non-Gaussian systems using minimizing error entropy criterion in [21]. In addition, the data-driven approach to control non-Gaussian systems was presented in [22], where an optimal control strategy was developed for semiconductor processes with non-Gaussian noise by using the minimum error entropy criterion. The PDF of tracking error and quadratic Renyi′s entropy were estimated directly using the Parzen windowing technology [23]. Nevertheless, the existed model free stochastic distribution control methods cannot cope with multivariable nonlinear non-Gaussian systems.

It has been pointed out that (h,ϕ)-entropy presented in [24] was a unification of entropy measures [25,26]. It is natural to investigate minimum entropy control method using (h,ϕ)-entropy rather than Shannon entropy or Renyi entropy. And it is known that the single neuron has some advantages in terms of simple algorithm and principle, easy implementation and real time ability. Therefore, in this paper, a single-neuron adaptive control algorithm is proposed for multivariate non-linear stochastic systems with non-Gaussian disturbances based on the minimum (h,ϕ)-entropy principle.

The remainder of this paper is organized as follows. Section 2 describes the problem and presents some information about the considered systems. In this section, the measurements of the input and output data rather than the analytical model are given. Section 3 provides a generalized (h,ϕ)-entropy criterion and its stochastic estimation using sliding window technology. The optimal control algorithm is then obtained by training the weighting matrix under the proposed criterion in Section 4. Section 5 gives the convergence condition of the designed control algorithm. Numerical simulation results are presented to illustrate the efficiency and validity of the given method in Section 6. Section 7 offers some concluding remarks on this investigation.

2. Problem formulation

It is usually difficult to formulate the mathematical model for general dynamic processes with nonlinearities and non-Gaussianities. Nevertheless, the measurements of the process output data and the set point are always available. Denote the measurement of the output and the corresponding control input as $y_k \in \Re^n$ and $u_k \in \Re^m$, respectively. Let $r_k \in \Re^n$ be the set point. We assume that the tracking error vector is bounded and denoted as $e_k = y_k - r_k \in [a,b]^n$.

Since the random noise is non-Gaussian, the tracking error e_k is also non-Gaussian. Even if the involved randomness is Gaussian, the nonlinearity of the system may lead a non-Gaussian tracking error. In this case, the well-known mean-square-error (MSE) criterion would become invalid. To overcome this problem, minimum-error-entropy (MEE) criterion has been used to deal with the control problems for nonlinear non-Gaussian stochastic systems (see e.g. [22]).

As mentioned in the introduction section, the (h,ϕ)-entropy [24–26], a unification of entropy measures, was used to construct the performance index for solving optimal tracking control solution. Based on the time series data of the system outputs and control inputs $I_k = \{y_{k-1}, \ldots, y_0, ; u_{k-1}, u_{k-2}, \ldots, u_0\}$, the optimal controller implemented by single neurons is designed by optimizing the performance index.

In the data-driven context, it is imperative to estimate the (h,ϕ)-entropy from the time series data e_k $(k=1,2,\ldots)$. And the convergent condition of the single neuron based controller also needs to be judged.

3. Performance index and the estimate of (h,ϕ)-entropy

In this section, the following minimum entropy criterion will be used to obtain neural control law

$$J_k = R_1 H_\phi^h(e_k) + \frac{1}{2} u_k^T R_2 u_k \tag{1}$$

where $R_1 \in \Re$ and $R_2 \in \Re^{m \times m}$ are the weights corresponding to entropy of the tracking error and control energy, respectively. $H_\phi^h(e_k)$ is the joint entropy of the n-dimensional tracking error e_k, which is defined by

$$H_\phi^h(e_k) = h\left(\int_{-\infty}^{\infty} \phi[\gamma_{e_k}(\xi)] d\xi\right) \tag{2}$$

where either $\phi : [0,\infty) \to R$ is concave and $h : R \to R$ is increasing, or $\phi : [0,\infty) \to R$ is convex and $h : R \to R$ is decreasing. In this paper, we shall assume that h and ϕ are differentiable up to second order over the entire extent of $(-\infty,+\infty)$ and $[0,\infty)$, respectively.γ_{e_k} is the joint PDF of the random vector e_k.

Next, we will show how to estimate the performance index by using the available information.

At instant k, (2) can be rewritten as

$$\begin{aligned} H_\phi^h(x) &= h\left(\int_{-\infty}^{\infty} \gamma_{e_k}(x) \times \frac{\phi[\gamma_{e_k}(x)]}{\gamma_{e_k}(x)} dx\right) \\ &= h\left(E\left\{\frac{\phi[\gamma_{e_k}(x)]}{\gamma_{e_k}(x)}\right\}\right) = h\left(E\left\{\psi\left[\gamma_{e_k}(x)\right]\right\}\right) \end{aligned} \tag{3}$$

where $\psi(z) = \phi(z)/z$, $E(\cdot)$ is the expectation operator.

We will drop the expectation from the definition of (h,ϕ)-entropy and use the most current sample of tracking error in the PDF to obtain the following stochastic estimate for (h,ϕ)-entropy:

$$H_\phi^h(e_k) = h(E\{\psi[\gamma_{e_k}(e_k)]\}) \approx h(\psi[\gamma_{e_k}(e_k)]) \tag{4}$$

where e_k denotes the most recent sample of tracking error at instant k. Since the joint PDF of tracking error e_k is usually unknown in practice, the "sliding window" technology shown in Fig. 1 is employed to estimate the joint PDF of tracking error over the most recent L samples $\vec{e}_{(k-L):(k-1)}$, where $\vec{e}_{a:b} = \{e_a, e_{a+1}, \ldots, e_b\}$ is the samples within the sliding window whose width is $L = b - a + 1$. When $k < L$, the data $\vec{e}_{(k-L):(k-1)}$ can be

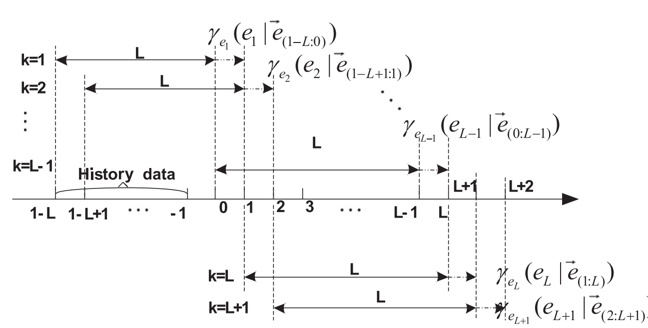

Fig. 1. Sliding window PDF estimation strategy.