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Performance evaluation of analog circuit using improved LSSVR subject to data information uncertainty

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ABSTRACT

This paper demystifies the proposed analog circuit performance evaluation methods based on improved LSSVR (ILSSVR) by examining the arithmetic speed and the evaluation reliability online. The ILSSVR performance evaluation scheme has the robustness for the signal information uncertainty, which may be deduced by nonlinear feature, time varying feature and contain faults value about industrial field data information. More specially, the self-update via incremental and reduced interaction is employed to detect the interests both on history data information and the updated data information, and the features extraction nonlinear independent component analysis (NICA) is proposed, then the number of the feature data is controlled and desired time consumed is guaranteed. In addition, the multi-kernel and weighted idea have also been employed to interfuse quite flexibility to the bandwidths of kernel online. The proposed analog circuit performance evaluation scheme ILSSVR is evaluated for two filter circuit: leapfrog filter circuit and self-adapting filter circuit. And the effectiveness is illustrated through a numerical example.

1. Introduction

Due to the overwhelming application of the analog circuit in electronic products, industry system as well as economic operation, modern technical processes become more complicated and the automation degrees of such systems are significantly growing. The safety and reliability issues on the complicated processes receive more attention and become the most critical factors in process design nowadays. On the other hand, the complete reliance on human operators to deal with abnormal events has become increasingly difficult as shown by the following facts: (1) It is impossible to define any unified fault model for analog circuits owing to the parameters of analog components are usually continuous. (2) In practical circuit under tests (CUTs), the information used in diagnostics is not sufficient because of lack of test node. (3) Tolerance effects of the analog components are difficult to eliminate [1–3]. Therefore, performance evaluation or fault diagnosis of analog circuits has become an active research; and now lots of schemes or theory have been introduced to this control system. Yin et al. [4] provide an overview of the recent developments in data-based techniques focused on modern industrial applications, and summarize the recent achievements in data-based techniques especially for complicated industrial applications. Nearly at the same time, he also addresses a review on basic data-driven approaches for industrial process monitoring [5]. Among Shen Yin's discussion about data-driven, a conclusion can be drawn that the data-driven, whether NNs or SVMs, feature selection methods have become an apparent need for circuit performance evaluation or fault diagnosis. And a basic data-driven design framework with necessary modification under various industrial operating conditions was sketched, aiming to offer a reference for industrial process monitoring on large-scale industrial processes. Similar issues are also discussed in Refs. [6–8]. Zhao et al. [9] proposed a robust control of continuous-time systems with state-dependent uncertainties and its application to electronic circuits. Moreover, Robust control has also been applied in this field. Aiming to the data information uncertainty, system robust was employed to deal with it. Literature [10] is a typical sample to solve the uncertainty with system robust. Some literatures [11,12] design the observers to observe the static or dynamic output feedback information, then the system state can be confirmed.

Although, all of the above methods can realize the performance evaluation of analog circuit, more attentions are paid to the data-driven methods. Support Vector Regression (SVR) as one of the data driven methods has been defined the extension of SVMs to solve regression and prediction problems. Yuvaraj et al. [13] studied this issue, and SVR had been successfully applied to predict fracture characteristics and failure load of high strength concrete and ultra-high strength concrete beams. However, it ignored the need of fast time responding. Aiming to this problem about time consumed,

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Acevedo-Rodrı´guez et al. [14] proposed a new method of reducing the computational load in decision functions provided by a support vector classification machine. This method could save 25–90% time consumed via exploiting the geometrical relations when the kernels adopted are based distances to obtain bounds of the remaining decision function and avoids to continue calculating kernel operations when there is no chance to change the decision. The defect of this method is that its second kernel still needs to obtain more support vectors.

Feature extraction is the important step in developing SVR or SVM [15]. Well feature extraction can guarantee the precision of performance or classification. Some researchers have focused on this issue, Guyon et al. [16] proposed recursive feature elimination method in SVM for feature selections. Weston et al. [17] proposed the use of gradient descent methods in SVM. Principal component analysis (PCA) and independent component analysis (ICA) are the well-known methods for feature extraction. By calculating the eigenvectors of the covariance matrix of the original in-puts, PCA linearly transforms a high-dimensional input vector into a low-dimensional one whose components are uncorrelated. ICA attempts to achieve statistically independent components in the transformed vectors and was originally developed for blind source separation and later generalized for feature extraction [18]. Here we employ NICA [19] to realize feature extraction.

The main contributions of this paper are: (1) self-update via incremental and reduced interaction is employed to detect the interests on both history data information and the updated data information, and the desired time consumed is guaranteed. (2) NICA is addressed in the features extraction in the context of ILSSVR prediction about analog circuit performance evaluation. (3) Multi-kernel and weighted value updated are employed to interfuse quite flexibility to the bandwidths of kernel online.

The rest of the paper is organized as follows. Firstly, the performance evaluation system is reported in Section 2. Then, Performance Evaluation based on ILSSVR method is introduced in Section 3. Next, the feature extraction methods and corresponding parameters optimized methods are introduced in Section 4. Numerical simulations are presented in Section 5. Finally, conclusion is outlined in Section 6.

2. Performance evaluation system

The proposed method is based on ILSSVR. Fig. 1 shows a block diagram of an analog circuit performance evaluation system, which consists of five modules: analog circuit, input/output data acquisition, signal transmission, feature extraction and performance analysis based on ILSSVR. The analog circuit module generates the input/output signal and drives the data acquisition module. At the same time, the defect signal which includes fault value, disturbance value will be accepted via the data acquisition and sent to feature extraction by the signal transmission module. Signal transmission module can realize the defect classification and quantification. Feature extraction plays a paramount influence in determining the evaluation precision about performance of analog circuit. When the unexpected signal is dropped in, the module of feature extraction will be disposed. Then the vital module, performance analysis based on ILSSVR, is driven. The key here mainly includes two modules: feature extraction and performance analysis based on SVR. The evaluation accuracy is bound up with handling information which includes unexpected values. For the purpose, three methods of feature extraction, (1) principal component analysis (PCA), (2) independent component analysis and (3) nonlinear frequency spectrum (NFS), are employed to prove the well performance not only for dealing with the unexpected values but also for extracting the useful feature parameter values. Additional, the evaluation accuracy is also closely connected with the module of performance analysis based improved SVR, meanwhile, the fast responding of performance evaluation also relies this module. In this paper, a novel performance evaluation method based on ILSSVR is proposed. For realizing comparison analysis about the proposed evaluation scheme, the traditional normal LSSVR, δ-LSSVR have also been employed in this paper.

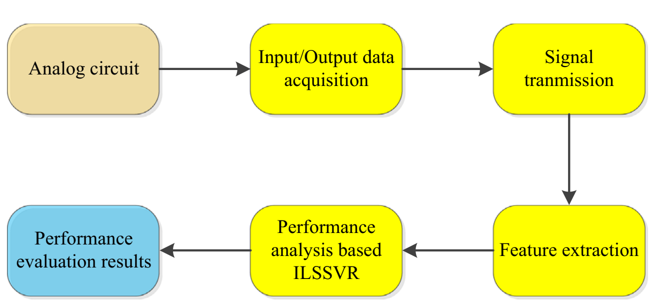

Fig. 1. Analog circuit performance evaluation model.

3. Performance evaluation based on ILSSVR

3.1. LSSVR

Given a set of S training data $s_i=\{(x_1,y_1),\cdots,(x_s,y_s)\}$ where $x_i\in R^n$, $i=1,\cdots,s$ are the input feature vectors with n dimension, $y_i\in R$ is the corresponding model output feature vectors. The normal least squares support vector regression is obtained by solving the following optimization problem [20]:

$$\min J(\boldsymbol{\omega},\boldsymbol{e},\boldsymbol{b})=\tfrac{1}{2}\|\boldsymbol{\omega}\|^2+\tfrac{1}{2}\gamma\sum_{i=1}^{S}e_i^2$$
$$\text{s.t.}\ y_i=\boldsymbol{\omega}\varphi(x_i)+\boldsymbol{b}+e_i\quad i=1,\cdots,s \tag{1}$$

where $J(\boldsymbol{\omega},\boldsymbol{e},\boldsymbol{b})$ is objective function, $\gamma\in R^+$ is the regularization parameter, $\boldsymbol{e}=(e_1,e_2,\cdots,e_S)^T$ denotes the prediction residual vector, and γ controls the penalty to $\boldsymbol{e}$, $\boldsymbol{\omega}$ is the normal vector of the hyperplane, b is the offset, $\varphi(x_i)$ is the mapping from the input space to the feature space. It is not hard to find in literatures [20,21], the constrained optimization problem is solved via Lagrangian multipliers under the Karush–Kuhn–Tucker (KKT) condition.

$$\boldsymbol{L}(\boldsymbol{\omega},\boldsymbol{e},b,\boldsymbol{\alpha})=\frac{1}{2}\|\boldsymbol{\omega}\|^2+\frac{1}{2}\gamma\sum_{i=1}^{S}\alpha_i(y_i-\boldsymbol{\omega}^T\varphi(x_i)-\boldsymbol{b}-e_i) \tag{2}$$

where $\boldsymbol{\alpha}$ is the Lagrangian multiplier vector. The conditions for the optimality can be obtained by solving the following partial derivatives:

$$\frac{\partial\boldsymbol{L}}{\partial\boldsymbol{\omega}}=0\rightarrow\boldsymbol{\omega}=\sum_{i=1}^{S}\alpha_i\varphi(x_i) \tag{3}$$

$$\frac{\partial\boldsymbol{L}}{\partial e_i}=0\rightarrow\alpha_i=\gamma e_i,\quad i=1,2,\cdots,S \tag{4}$$

$$\frac{\partial\boldsymbol{L}}{\partial\boldsymbol{b}}=0\rightarrow\sum_{i=1}^{S}\alpha_i=0 \tag{5}$$

$$\frac{\partial\boldsymbol{L}}{\partial\alpha_i}=0\rightarrow\boldsymbol{\omega}^T\varphi(x_i)+\boldsymbol{b}+e_i-\boldsymbol{y}_i=0,\quad i=1,2,\cdots,S \tag{6}$$

LSSVR expects to obtain the estimation formulation like the same format as $y_i=\boldsymbol{\omega}\varphi(x_i)+\boldsymbol{b}$ to realize estimate and diagnosis for future samples. However, the feature function $\varphi(x_i)$ is difficult to be confirmed. Here we adopt Lagrangian multiplier and matrix transform to solve the problem, then the vectors $\boldsymbol{\omega}$ and $\boldsymbol{e}$ are eliminated, the optimization problem can be transformed as following linear equations set:

$$\begin{bmatrix}\boldsymbol{0} & \boldsymbol{1}^T\\ \boldsymbol{1} & \boldsymbol{A}\end{bmatrix}\begin{bmatrix}\boldsymbol{b}\\ \boldsymbol{\alpha}\end{bmatrix}=\begin{bmatrix}\boldsymbol{0}\\ \boldsymbol{y}\end{bmatrix} \tag{7}$$