Research of Sensor Fault-Tolerant Control Based on CSA-SVR Algorithm for EMB Actuator System

Yuxue Wang, Yinan Xu, Yihu Xu, and Yonghu Ma

***Abstract*—The electro mechanical brake (EMB) system is a efficient pure electric vehicle braking system in where technologies in the fields of electronics, mechanics, and vehicle communication network were considered at the same time. Because that offered information to the electronic control of the EMB system is taken from several detectors, during developments of the pure electric vehicle, unsolved difficulties in EMB system are the accurate fault detection as well as the timely process of a fault tolerant control. In this paper, the fault detection and the fault tolerant control on the mathematical models of a current, a speed, and a pressure detector loaded on the EMB actuator system will be studied. Based on the three-loop control architecture model of the EMB actuator, these models of detectors are constructed by the method of the dynamics analysis of the actuating agency respectively. On the purpose of improving the accuracy of fault detection, the clonal selection - support vector regression algorithm (CSA-SVR) is proposed, which is a combination of CSA and SVR calculation methods. Through CSA-SVR algorithm, optimized parameters of support vector machine (SVM) and improved accuracy of fault detection are obtained. The adaptive fault tolerant control architectural model mentioned which is designed using CSA-SVR algorithm in this paper shows effective function in fault detection, isolation from fault, and fault estimation.**

***Index Terms*—Electro mechanical brake, fault diagnosis, fault reconstruction, support vector machine, clonal selection algorithm.**

I. Introduction

The electro mechanical brake (EMB) system is one direct reason of electric vehicle's breaking function, Which is the key technology for fundamentally improving the driving stabilization, comfortableness, and economics of energy consumption in the electric vehicle [1]. EMB actuators are composed of retarding mechanisms, movement conversion devices, and executive motors mainly [2]. EMB actuators are loaded with various detectors like detecting currents, speeds, and pressures which are used for information perception, detection and obtainment. Obviously, if there is something wrong in detectors, there will no detection of driver's brake intention and no reliable breaking effect. Hence, for the purpose of improving the robustness of the breaking system, the study of fault detection and fault tolerant control of sensors in EMB actuator is especially important.

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In the previous studies of sensor fault detection, one kind of kalman filter was designed and published by Gao [3] which could detect sensor's fault effectively. However, such a method is suitable for liner system only. There is another reference [4] that mentions fault detection methods based on the BP neural network calculation. As well as, in the reference [5], the calculation method based on wavelet neural network is mentioned which can resolve the sensor fault like from temperature, flow rate, and pressure in the variable air volume (VAV) system. Above researches show that the neural network calculation method has realized functions of self-learning, parallel processing, and fault tolerance. However, neural network calculations need huge training sample, have complex constructions, and show poor real time performance. Such over fitting phenomena will cause low generalization ability.

Through studies of fault tolerant control, fault diagnosis, control and observer are established using neural network calculation and BP neural network calculation as stated in references [6] and [7]. According to them, under the fault occurrence, information from fault sensor will be replaced by information from tolerant control system. However, disadvantages are that it is depending on the initial value settings, easy to sink into local extremum, and causing over fitting.

The rest of the paper is organized as follows: In Section II, the mathematical model for EMB actuator is proposed. In Section III, CSA-SVR fault detection method is mentioned which is the combination of SVM and CSA algorithms and parameters of SVM was optimized. In Section IV and Section V, the fault tolerant control architectural model of sensors in EMB actuator systems is mentioned using CSA-SVR algorithm. Concluding remarks are given in Section VI.

II. Mathematical Model of the EMB Actuator

Three main compositions of EMB actuator system are a retarding mechanism, a movement conversion device, and an executive motor. Fig. 1 shows the three-loop control architecture model for EMB actuator. In this paper, three controls indicate pressure, speed, and current signals, These information is taken from the implementation of the executive motors [8]-[10].

Whether the EMB actuator operates normally or not largely depends on the accuracy of information obtained from current, speed, and pressure sensors. Current and speed information come from the brushless direct current motor (BDCM) in EMB system while pressure information comes from the brake caliper. The output model of current and speed sensors are established using the mathematical model of BDCM [11]. The output model of the pressure sensor is

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established through the mechanical relationship between a force and a load torque.

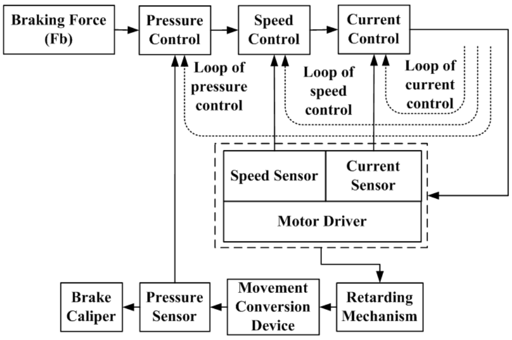

Fig. 1. Three-loop control architecture model for EMB actuator.

When BDCM is normal, states of BDCM are expressed as bellow:

$$\begin{bmatrix} u_a \\ u_b \\ u_c \end{bmatrix} = \begin{bmatrix} r_1 & 0 & 0 \\ 0 & r_2 & 0 \\ 0 & 0 & r_3 \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} L_s & L_m & L_m \\ L_m & L_s & L_m \\ L_m & L_m & L_s \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad (1)$$

Among the formula 1, L_s is a self-inductance of stator winding, L_m is a mutual-inductor between any two stator windings. Based on Kirchhoff voltage Law (KVL), a voltage expression in the motor circuit is:

$$E_a = Ri + L\frac{di}{dt} + e \quad (2)$$

Here, E_a is an armature voltage, e is an armature counter electromotive force, I is an armature current, L is an armature inductance, R is an armature resistance.

The counter electromotive force of the stator winding is proportional to the rotor acceleration. The expression can be shown as:

$$e = K_e \cdot \omega_m \quad (3)$$

In formula 3, K_e and ω_m indicate a counter electromotive force coefficient and corner respectively.

An electromagnetic torque generated in a stator winding is:

$$T_{em} = \frac{e_a i_a + e_b i_b + e_c i_c}{\omega_m} = K_T \cdot i \quad (4)$$

Here, K_T is a torque coefficient.

The kinetic equation of BDCM is:

$$T_{em} = K_f \omega_m + J\frac{d\omega_m}{dt} + T_L \quad (5)$$

Here, K_f is a friction factor, J is a inertia load, T_L is a motor load torque.

$$\frac{di}{dt} = \frac{E_a}{L} - i\frac{R}{L} - \frac{K_e}{L}\omega_m \quad (6)$$

$$\frac{d\omega_m}{dt} = \frac{T_L}{J} - i\frac{K_T}{J} - \frac{K_f}{J}\omega_m \quad (7)$$

Based on the physical structure of the EMB actuator, the relationship between a braking force and a motor load torque is expressed as formula 8:

$$F = \frac{T/R_m}{C} \quad (8)$$

Here, F, C, R_m, and T are braking force, the brake efficiency factor, brake disc radius, and braking torque, respectively.

III. Sensor Fault Detection Model Based on CSA-AVR Algorithm

As a powerful mechanical studying method, SVM algorithm is reported by V. Vapnik etc.. That is widely used in fields of a regression and a functional approximation with the function of overcoming a dimension curse.

During constructing a regression prediction model, SVM algorithm approximates a real function through studying given samples. We can choose appropriate solution parameters ($\varepsilon > 0$), penalty parameter ($C > 0$), and kernel function ($K(x, x')$), to construct and optimize.

$$\min_{\alpha^{(*)} \in R^{2l}} \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)K(x_i, x_j) + \varepsilon\sum_{i=1}^{l}(\alpha_i^* - \alpha_i) - \sum_{i=1}^{l} y_i(\alpha_i^* - \alpha_i)$$

$$s.t. \quad \sum_{i=1}^{l}(\alpha_i^* - \alpha_i) = 0$$
$$0 \le \alpha_i, \quad \alpha_i^* \le \frac{C}{l}, \quad i = 1, \cdots, l \quad (9)$$

The optimal solution, $\bar{\alpha}^{(*)} = (\bar{\alpha}_1, \bar{\alpha}_1^*, \cdots, \bar{\alpha}_l, \bar{\alpha}_l^*)^T$ is obtained from formula 9. The positive component $\bar{\alpha}^{(*)}$($\bar{\alpha}_j > 0$) was chosen to calculate $\bar{b} = y_i - \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)K(x_i, x_j) + \varepsilon$. The construction of the decision is used to expect unknown samples.

$$y = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)K(x_i, x_j) + \bar{b} \quad (10)$$

The quality of SVM depends on selected kernel parameters and penalty parameters of SVM. The accuracy of the regression model that is constructed using previous parameters, is difficult to realize intelligent fault detection and fault tolerant control in the nonlinear system. In clonal selection algorithm, mechanisms like genetic recombination, affinity maturation, and receptor editing are more appropriate to show the better parameters search process [12], [13]. In order to select best kernel parameter and penalty parameter in SVR algorithm, optimizing SVM parameters method based on clonal selection calculation is mentioned in this research, as well as, by using CSA-SVR algorithm, the detection model of sensor fault detection is established. Fig. 2 shows flow chart of parameters optimization based on clonal selection algorithm.

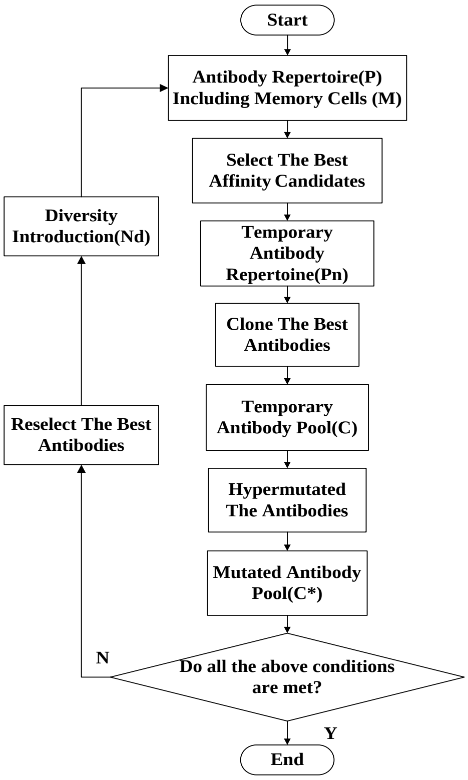

Fig. 2. Flow chart of parameters optimization.

SVM parameters optimization method based on CSA is realized by the consideration of SVM parameters optimization process, antigen recognizing and antibody evolution process in immune system together. Firstly, CSA parameters including evolution algebra, crossover probability, and mutation probability should be set. Select the random antibody and let randomly generated initial antibodies of CSA be decoded as the kernel and punishment parameter. The K-fold cross-validation method is used to calculate the correct classification rate of the antibody. Then, depending on the accuracy rate of classification to the testing samples, antibodies among the antibody repertoire are dealt with selective clone, crossover, and mutation operation. Finally, optimal affinity antibody will be outputted and corresponding kernel function and penalty parameter will be obtained. Obtained parameters will be input into SVR algorism to construct an approximation model of sensors. Fault detection of sensors will be realized by residual values of approximation outputs and real outputs of sensors. EMB actuator fault detection and architecture model are shown in Fig. 3.

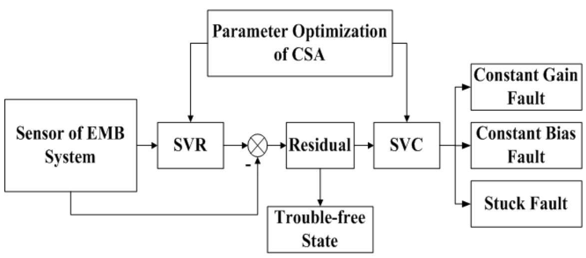

Fig. 3. Fault detection and diagnosis architecture model for EMB actuator.

IV. Adaptive Fault-Tolerant Control Model

When a fault is detected by fault detector, the adaptive fault tolerant control method can be used for further improvement of the reliability for EMB actuator. In this research, mathematical models of formula 6-8 and decision function shown in formula 10 are used to construct the fault reconstruction models of current, speed, and pressure sensors respectively.

When constructing a speed sensor reconstruction model, signals from current and pressure sensors are used to estimate signals from speed sensor. The speed sensor reconstruction model is shown as follow:

$$\hat{\omega}_k = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)K(I_{k-1}, F_{k-1}) + \bar{b} \tag{11}$$

where, k is a fault occurring moment in sensors, l is sampling interval before fault occurrence. The pressure reconstruction model can be written as follows:

$$\hat{F}_k = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)K(I_{k-1}, \omega_{k-1}) + \bar{b} \tag{12}$$

The current reconstruction model can be written as follows:

$$\hat{I}_k = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)K(\omega_{k-1}, F_{k-1}) + \bar{b} \tag{13}$$

Among above formulations, K indicates radial basis function.

$$k(x \cdot y) = \exp(-\frac{\|x-y\|^2}{s^2}) \tag{14}$$

where, s is a kernel function. Through above reconstruction, another fault sensor signal could be estimated from both of mathematical models in EMB actuator and normal working sensor.

As shown in Fig. 4, a sensor adaptive fault-tolerant control model for EMB actuator is established using fault detection models and reconstruction models of three kinds of sensors.

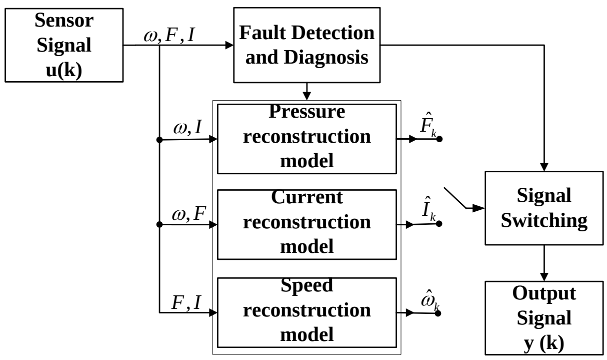

Fig. 4. Sensor adaptive fault-tolerant control model for EMB actuator.

As shown in Fig. 4, input signals of current, speed, and pressure from EMB actuator are imported into the fault detection and reconstruction model of various sensors.

Through detecting fault from fault detector, output detection signals are transformed to the reconstruction model and the signal switching model in each sensor. Reconstruction model of each sensor estimates the signal of fault detector based on signals from normal working two sensors. When sensor faults occur, on the purpose of realizing adaptive fault tolerant control, the output signal from fault detector will be blocked by the signal switching model and estimated signals from reconstruction model will replace signals from fault detector.

V. Simulation Result

In order to confirm the reliability of the adaptive fault tolerant control architectural model, simulations are carried out against to current, speed, and pressure sensors of EMB actuator under MATLAB environment. Parameters of clonal selection algorithm are shown in Table I.

TABLE I: Parameters of Clonal Selection Algorithm

Patameter	Value
Antibodies scale	20
Encoding length	10
Encoding length (Pc)	0.2
Mutation rate (Pm)	0.01
Selected individual number (m)	12
Proportional control factor	0.2
Antibody concentration threshold	0.6
Evolution generation	100

Fig. 5-Fig. 7 are stuck fault of detecting sensors, constant gain fault, and constant bias fault respectively.

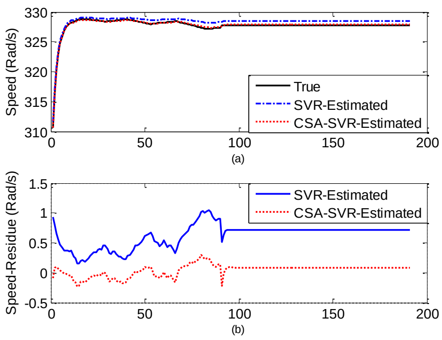

Fig. 5. Sensor stuck fault signal detection and estimation.

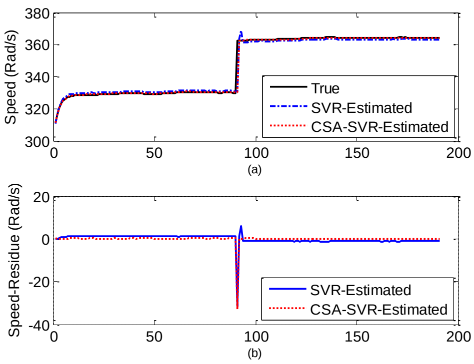

Fig. 6. Sensor constant gain fault signal detection and estimation.

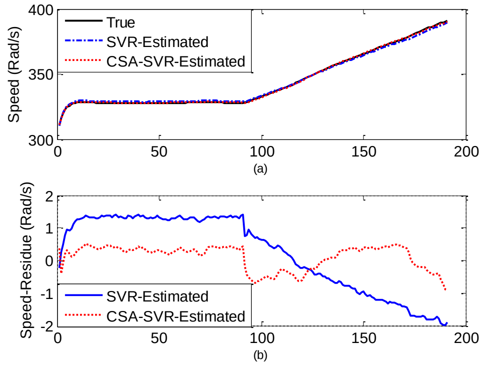

Fig. 7. Sensor constant bias fault signal detection and estimation.

In Fig.5-Fig. 7, figures (a) indicate real output of sensors and comparison pictures of estimated outputs from SVR and CSA-SVR algorism. Figures (b) indicate residual comparison pictures of SVR and CSA-SVR algorism. From simulation results, when a sensor fault occurs, it is observed that there are obvious jumps in the residual wave between real output values and estimated output values. Fault detection model based on CSA-SVR algorism is more accurate than traditional SVR fault detection model.

If a fault from fault sensor were detected, output signals of fault detector would be blocked by switching model and replaced by compensated output signals from reconstruction model. Fig. 8-Fig. 10 show fault reconstructions of sensors and deviation comparison pictures.

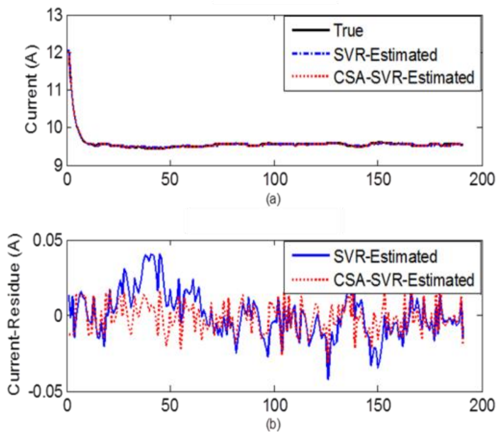

Fig. 8. Current sensor reconstruction and error comparison diagram.

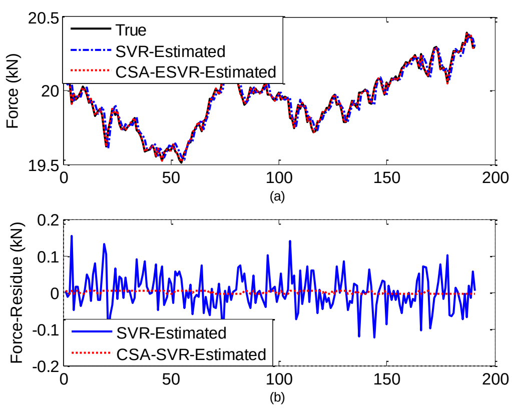

Fig. 9. Pressure sensor reconstruction and error comparison diagram.

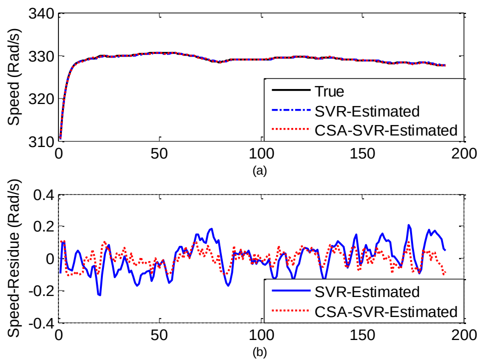

Fig. 10. Speed sensor reconstruction and error comparison diagram.

In Fig.8-Fig. 10, figures (a) indicate real output of sensors and comparison pictures of estimated outputs from SVR and CSA-SVR algorism. Figures (b) indicate residual comparison pictures of SVR and CSA-SVR algorism.

From simulation results, estimated output signal using reconstruction model of CSA-SVR algorism is more accurate than traditional reconstruction model of SVR fault detection model.

VI. Conclusion

In this research, fault tolerant control architectural model of sensors based on CSA-SVR algorism is proposed. Firstly, mathematical models of three kinds of sensors like current, speed, and pressure sensors in the EMB actuator are established. Next, through CSA-SVR algorism, sensor fault detection model is constructed. As well as, the residual between real signal and estimated signal is used to detect fault. Finally, using CSA-SVR algorism, one kind of adaptive fault tolerant control is designed. Consequently, the quality of fault detection and fault tolerant control models in EMB actuator system is improved.

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