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Adaptive Fuzzy-Neuro-Wavelet Dynamic Sliding-Mode Control for a BLDC Motor

Chun-Fei Hsu, and Kai-Lin Peng

***Abstract*—In this paper, an adaptive fuzzy-neuro-wavelet dynamic sliding-mode control (AFDSC) system which is composed of a neural controller and a switching compensator is proposed. The neural controller using a fuzzy wavelet neural network is the main controller, and the switching compensator is designed to eliminate the approximation error introduced by neural controller. The adaptation laws of the AFDSC system are derived in the sense of Lyapunov function, thus the system can be guaranteed to be stable. Finally, the proposed AFDSC system is implemented based on a field programmable gate array (FPGA) chip for low-cost and high-performance industrial applications and it is applied to control a brushless DC (BLDC) motor. The experimental results demonstrate the proposed AFDSC scheme can achieve favorable control performance without occurring chattering phenomena.**

***Index Terms*—adaptive control, neural control, sliding-mode control, wavelet neural network, BLDC motor.**

I. Introduction

It is well known that the major advantage of sliding-mode control (SMC) systems is its insensitivity to parameter variations and external disturbance once the system trajectory reaches and stays on the sliding surface [1]. However, the SMC strategy produces some drawbacks associated with the large control chattering which is caused by a switching function in the control law. It may wear coupled mechanisms and excite unstable system dynamics. To tackle this problem, among several kinds of the SMC systems, the dynamic sliding-mode control (DSMC) system is an effective control scheme for chattering eliminating [2, 3]. The additional dynamics can be considered as compensators that are designed for improving the sliding-mode stability. Due to DSMC using integration method to obtain the practical control effort, the chattering phenomenon can be improved effectively.

Since the dynamic characteristic of control plants are nonlinear and the precise models are difficult to obtain, the model-based control approaches such as SMC and DSMC are difficult to be implemented. Many intelligent control schemes such as adaptive neural network control [4-6] have been developed. The most useful property is their ability of neural networks can approximate arbitrary linear or nonlinear mapping through learning [4]. Some researchers have developed the structure of neural network based on the wavelet functions to construct the wavelet neural network (WNN) [7]. Unlike the sigmoidal functions used in conventional neural networks, wavelet functions are spatially localized, so that the learning capability of WNN is more efficient than the conventional neural network for system identification.

Motivated by this merit, a fuzzy wavelet neural network (FWNN) is proposed [8]. The proposed FWNN has superior capability to the conventional WNN in an efficient learning mechanism. Up to now, there has been considerable interest in exploring the applications of WNN and FWNN to deal with nonlinearity and uncertainties of real-time adaptive control system [9-13]. In order to ensure the stability of the closed-loop control system, a switching compensator is designed to dispel the approximation error. However, it will result substantial chattering in the control effort [10].

In this paper, an adaptive fuzzy-neuro-wavelet dynamic sliding-mode control (AFDSC) system which is composed of a neural controller and a switching compensator is proposed. A dynamic sliding surface is proposed to reduce the chattering phenomenon. The neural controller using a FWNN is the main controller, and the switching compensator is designed to eliminate the approximation error introduced by neural controller. Moreover, the adaptation laws of the control system are derived in the sense of Lyapunov function and Barbalat's lemma, thus the system can be guaranteed to be asymptotically stable. Finally, the proposed AFDSC system is implemented based on a field-programmable gate array (FPGA) chip for low-cost and high-performance industrial applications and applied to control a brushless DC (BLDC) motor to show its effectiveness. The experimental results verify the system stabilization, favorable tracking performance and no chattering phenomena can be achieved by the proposed AFDSC system.

II. Problem Formulation

The brushless DC (BLDC) motor can be represented in the following form [14]

$$\ddot{\theta}(t) = -\frac{B}{J}\dot{\theta}(t) + \frac{K_t}{J}u(t) = f(\theta,t) + gu(t) \qquad (1)$$

where J is the moment of inertia; B is the damping coefficient; K_t is the torque constant; $f(\theta,t) = -\frac{B}{J}\dot{\theta}(t)$; $g = \frac{K_t}{J}$ is a constant control gain and $u(t)$ is the control effort. The nominal model of the BLDC motor can be represented as

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$$\ddot{\theta}(t) = f_n(\theta,t) + g_n u(t) \tag{2}$$

where $f_n(\theta,t)$ and g_n are the mapping that represent the nominal behavior of $f(\theta,t)$ and g, respectively. If the system uncertainties occur and the external disturbance is added, the system dynamic is modified as

$$\begin{aligned}\ddot{\theta}(t) &= [f_n(\theta,t) + \Delta f(t)] + (g_n + \Delta g)u(t) + d(t) \\ &= f_n(\theta,t) + g_n u(t) + w(t)\end{aligned} \tag{3}$$

where $\Delta f(t)$ and Δg denote the system uncertainties; $d(t)$ is the external disturbance; and $w(t)$ is called the lumped uncertainty which defined as $w(t) = \Delta f(t) + \Delta g u(t) + d(t)$. The control objective of the BLDC motor is to find a control law so that the rotor position $\theta(t)$ can track the position command $\theta_c(t)$ closely. Define the tracking error as

$$e(t) = \theta_c(t) - \theta(t) \tag{4}$$

And, a sliding surface is defined as [1]

$$s(t) = \dot{e}(t) + a_1 e(t) + a_2 \int_0^t e(\tau)d\tau \tag{5}$$

where a_1 and a_2 are positive constants. In order to reduce the chattering phenomenon, a dynamic sliding surface defined as [2]

$$\varsigma(t) = \dot{s}(t) + b_1 s(t) + b_2 \int_0^t s(\tau)d\tau \tag{6}$$

where b_1 and b_2 are positive constants. Differentiating (6) with respect to time and using (4) and (5) obtain

$$\begin{aligned}\dot{\varsigma}(t) &= \ddot{s}(t) + b_1\dot{s}(t) + b_2 s(t) \\ &= \dddot{\theta}_c(t) - \dot{f}_n(\theta,t) - g_n\dot{u}(t) - \dot{w}(t) + c_1\ddot{e}(t) + c_2\dot{e}(t) + c_3 e(t) + c_4\int_0^t e(\tau)d\tau\end{aligned} \tag{7}$$

where $c_1 = a_1 + b_1$, $c_2 = a_2 + a_1 b_1 + b_2$, $c_3 = a_2 b_1 + a_1 b_2$ and $c_4 = a_2 b_2$. The control law of DSMC is given as

$$u_{dsmc}(t) = \int_0^t \dot{u}_{dsmc}(\tau)d\tau \tag{8}$$

$$\begin{aligned}\dot{u}_{dsmc}(t) = g_n^{-1}[&-\dot{f}_n(\theta,t) + \dddot{\theta}_c(t) + c_1\ddot{e}(t) + c_2\dot{e}(t) + c_3 e(t) \\ &+ c_4\int_0^t e(\tau)d\tau + W\,\mathrm{sgn}(\varsigma(t))]\end{aligned} \tag{9}$$

where W is a given positive constant with the assumption $|\dot{w}(t)| \le W$. The control law of DSMC in (9) can guarantee the stability in the sense of the Lyapunov theorem [2, 3].

III. Design of AFDSC System

A. Description of FWNN

Based on the rigorous multi-resolution wavelet theory, a fuzzy inference system with some minor restrictions and modifications can function as the discrete wavelet transform [8]. Different from WNNs, fuzzy wavelet basis functions can be specified by experts as traditional fuzzy systems. The network structure of the FWNN can be considered as multi-layer feedforward neural network as shown in Fig. 1. Assume that there are *m* rules in FWNN can be described as [8]

Rule *i*: If x_1 is A_1^i and … and x_n is A_n^i,

Then y is $\alpha_i \psi_i(\mathbf{x})$ (10)

where $\mathbf{x} = [x_1\ x_2\ \dots\ x_n]^T$ and y are the input and output variables of FWNN, respectively; A_n^i are the linguistic terms characterized by their corresponding fuzzy membership functions of the fuzzy sets; and $\alpha_i \psi_i(\mathbf{x})$ is the output weight. $\psi_i(\mathbf{x}) = \prod_{k=1}^{n}(1 - \omega_{ki}^2 x_k^2)$ is defined as the "Mexican hat" mother wavelet function. Then, the FWNN performs the mappings according to

$$y = \sum_{i=1}^{m} \alpha_i \psi_i(\mathbf{x}) \varphi_i(\boldsymbol{\sigma}_i, \|\mathbf{x} - \mathbf{m}_i\|) \tag{11}$$

where $\mathbf{m}_i = [m_{1i}\ m_{2i}\ \dots\ m_{ni}]$ and $\boldsymbol{\sigma}_i = [\sigma_{1i}\ \sigma_{2i}\ \dots\ \sigma_{ni}]$ are the parameter vectors of the Gaussian membership, respectively. The Gaussian membership ϕ_i represents as

$$\varphi_i(\boldsymbol{\sigma}_i, \|x_j - \mathbf{m}_i\|) = \prod_{j=1}^{n} \exp[-(x_j - m_{ji})^2 \sigma_{ji}^{\ 2}] \tag{12}$$

where σ_{ji} and m_{ji} are the inverse of width and center of the Gaussian function in the *i*-th term of the *j*-th input linguistic variable, respectively. For ease of notation, (11) can be expressed in a compact vector form as

$$y = \boldsymbol{\alpha}^T \boldsymbol{\varphi}(\mathbf{x}, \mathbf{m}, \boldsymbol{\sigma}) \tag{13}$$

where $\boldsymbol{\alpha} = [\alpha_1\ \alpha_2\ \dots\ \alpha_m]^T$, $\boldsymbol{\varphi} = [\psi_1\varphi_1\ \psi_2\varphi_2\ \dots\ \psi_m\varphi_m]^T$, $\mathbf{m} = [\mathbf{m}_1\ \mathbf{m}_2\ \dots \mathbf{m}_m]^T$ and $\boldsymbol{\sigma} = [\boldsymbol{\sigma}_1\ \boldsymbol{\sigma}_2\ \dots\ \boldsymbol{\sigma}_m]^T$. By the universal approximation theorem, there exists an ideal FWNN identifier such that [8]

$$\Omega = y^* + \Delta = \boldsymbol{\alpha}^{*T} \boldsymbol{\varphi}^*(\mathbf{x}, \mathbf{m}^*, \boldsymbol{\sigma}^*) + \Delta \tag{14}$$

where $\boldsymbol{\alpha}^*$ and $\boldsymbol{\varphi}^*$ are optimal parameter vectors of $\boldsymbol{\alpha}$ and $\boldsymbol{\varphi}$, respectively; $\mathbf{m}^*$ and $\boldsymbol{\sigma}^*$ are optimal parameter vectors of $\mathbf{m}$ and $\boldsymbol{\sigma}$, respectively; and Δ is the approximation error. However, the optimal parameter vectors are unknown, so it is necessary to estimate the values. Define an estimative function

$$\hat{y} = \hat{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\varphi}}(\mathbf{x}, \hat{\mathbf{m}}, \hat{\boldsymbol{\sigma}}) \tag{15}$$

where $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\varphi}}$ are optimal parameter vectors of $\boldsymbol{\alpha}$ and $\boldsymbol{\varphi}$, respectively; and $\hat{\mathbf{m}}$ and $\hat{\boldsymbol{\sigma}}$ are optimal parameter vectors of $\mathbf{m}$ and $\boldsymbol{\sigma}$, respectively. Define the estimation error as

$$\tilde{y} = \Omega - \hat{\Xi} = \tilde{\boldsymbol{\alpha}}^T \tilde{\boldsymbol{\varphi}} + \hat{\boldsymbol{\alpha}}^T \tilde{\boldsymbol{\varphi}} + \tilde{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\varphi}} + \Delta \tag{16}$$

where $\tilde{\boldsymbol{\alpha}} = \boldsymbol{\alpha}^* - \hat{\boldsymbol{\alpha}}$ and $\tilde{\boldsymbol{\varphi}} = \boldsymbol{\varphi}^* - \hat{\boldsymbol{\varphi}}$. The Taylor expansion linearization technique is employed such that [10]

$$\tilde{\boldsymbol{\varphi}} = \mathbf{A}^T \tilde{\mathbf{m}} + \mathbf{B}^T \tilde{\boldsymbol{\sigma}} + \mathbf{h} \tag{17}$$

where $\tilde{\mathbf{m}} = \mathbf{m}^* - \hat{\mathbf{m}}$; $\tilde{\boldsymbol{\sigma}} = \boldsymbol{\sigma}^* - \hat{\boldsymbol{\sigma}}$ and $\mathbf{h}$ denotes the high-order term. Substitute (17) into (16), it can obtain that

$$\tilde{y} = \tilde{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T \mathbf{A} \hat{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\sigma}}^T \mathbf{B} \hat{\boldsymbol{\alpha}} + \varepsilon \tag{18}$$

where the uncertain $\varepsilon = \hat{\boldsymbol{\alpha}}^T \mathbf{h} + \tilde{\boldsymbol{\alpha}}^T \tilde{\boldsymbol{\varphi}} + \Delta$ is assumed to be bounded by $|\varepsilon| \le E$.

B. AFDSC System

The controller output of the proposed AFDSC system as shown in Fig. 2 is defined as

$$\dot{u}_{adsnc} = \dot{\hat{u}}_{nc} + \dot{\hat{u}}_{sc} \tag{19}$$

The neural controller $\dot{\hat{u}}_{nc}$ uses a FWNN to approximate the DSMC controller $u_{dsmc}(t)$ in (9), and the switching

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compensator $\dot{\hat{u}}_{sc}$ is utilized to compensate the approximation error introduced by the neural controller. Substituting (19) into (7) and using (9) and (18), yields

$$\dot{\varsigma} = g_n(\tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\mathbf{A}\hat{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\sigma}}^T\mathbf{B}\hat{\boldsymbol{\alpha}} + \varepsilon - \dot{\hat{u}}_{sc}) - \dot{w} - W\,\mathrm{sgn}(\varsigma) \quad (20)$$

To proof the stability of the AFDSC system, define a Lyapunov function candidate in the following form

$$V = \frac{1}{2}\varsigma^2 + g_n(\frac{1}{2\eta_\alpha}\tilde{\boldsymbol{\alpha}}^T\tilde{\boldsymbol{\alpha}} + \frac{1}{2\eta_m}\tilde{\mathbf{m}}^T\tilde{\mathbf{m}} + \frac{1}{2\eta_\sigma}\tilde{\boldsymbol{\sigma}}^T\tilde{\boldsymbol{\sigma}}) \quad (21)$$

where η_α, η_m, η_σ and η_r are positive constants. Taking the derivative of Lyapunov function in (21) and using (20), yields

$$\begin{aligned}\dot{V} &= \varsigma\dot{\varsigma} + g_n(\frac{1}{\eta_\alpha}\tilde{\boldsymbol{\alpha}}^T\dot{\tilde{\boldsymbol{\alpha}}} + \frac{1}{\eta_m}\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}} + \frac{1}{\eta_\sigma}\tilde{\boldsymbol{\sigma}}^T\dot{\tilde{\boldsymbol{\sigma}}}) \\ &= \varsigma g_n(\tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\mathbf{A}\hat{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\sigma}}^T\mathbf{B}\hat{\boldsymbol{\alpha}} + \varepsilon - \dot{\hat{u}}_{fc}) - \varsigma\dot{w} - W|\varsigma| \\ &\quad + g_n(\frac{\tilde{\boldsymbol{\alpha}}^T\dot{\tilde{\boldsymbol{\alpha}}}}{\eta_\alpha} + \frac{\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}}}{\eta_m} + \frac{\tilde{\boldsymbol{\sigma}}^T\dot{\tilde{\boldsymbol{\sigma}}}}{\eta_\sigma}) \\ &= g_n\tilde{\boldsymbol{\alpha}}^T(\varsigma\hat{\boldsymbol{\varphi}} + \frac{\dot{\tilde{\boldsymbol{\alpha}}}}{\eta_\alpha}) + \tilde{\mathbf{m}}^T(\varsigma\mathbf{A}\hat{\boldsymbol{\alpha}} + \frac{\dot{\tilde{\mathbf{m}}}}{\eta_m}) + \tilde{\boldsymbol{\sigma}}^T(\varsigma\mathbf{B}\hat{\boldsymbol{\alpha}} + \frac{\dot{\tilde{\boldsymbol{\sigma}}}}{\eta_\sigma}) \\ &\quad + g_n\varsigma(\varepsilon - \dot{\hat{u}}_{sc}) - \dot{w}\varsigma - W|\varsigma| \end{aligned} \quad (22)$$

If the adaptation laws are selected as

$$\dot{\hat{\boldsymbol{\alpha}}} = -\dot{\tilde{\boldsymbol{\alpha}}} = \eta_\alpha\varsigma\hat{\boldsymbol{\varphi}} \quad (23)$$

$$\dot{\hat{\mathbf{m}}} = -\dot{\tilde{\mathbf{m}}} = \eta_m\varsigma\mathbf{A}\hat{\boldsymbol{\alpha}} \quad (24)$$

$$\dot{\hat{\boldsymbol{\sigma}}} = -\dot{\tilde{\boldsymbol{\sigma}}} = \eta_\sigma\varsigma\mathbf{B}\hat{\boldsymbol{\alpha}} \quad (25)$$

and switching compensator is designed as

$$\dot{\hat{u}}_{sc} = E\,\mathrm{sgn}(\varsigma) \quad (26)$$

then equation (22) can be rewritten as

$$\begin{aligned}\dot{V} &= g_n(\varepsilon\varsigma - E|\varsigma|) - \varsigma\dot{w} - W|\varsigma| \\ &\le g_n(|\varepsilon||\varsigma| - E|\varsigma|) + |\dot{w}||\varsigma| - W|\varsigma| \\ &= -g_n(E - |\varepsilon|)|\varsigma| - (W - |\dot{w}|)|\varsigma| \le 0 \end{aligned} \quad (27)$$

By Barbalat's lemma, it can be concluded that $\varsigma \to 0$ as $t \to \infty$ [1]. As a result, the stability of the proposed adaptive fuzzy-neuro-wavelet dynamic sliding-mode control (AFDSC) system can be guaranteed.

IV. Experimental Results

A field-programmable gate array (FPGA) incorporates the architecture of gate arrays and the programmability of a programmable logic device. It consists of thousands of logic gates, some of which are combined together to form a configurable logic block thereby simplifying high-level circuit design. All the internal logic elements and all the control procedures of the FPGA are executed continuously and simultaneously [15]. If the control algorithm is executed sequentially using software in a digital signal processor (DSP) or personal computer (PC), the minimum execution time is limited. Therefore, the execution time of the FPGA is faster than either a DSP or PC. The circuits and algorithms can be developed in the very high speed integrated circuit hardware description language [15].

The experimental setup is shown in Fig. 3. This study used the Altera Stratix II series FPGA chip, and the Altera Quartus II software and the verilog hardware description language are used to implement the hardware control system. The Quartus II software is the development tool for programmable logic devices. The Nios II processor is a configurable, versatile, RISC embedded processor. It can be embedded into Altera FPGA, and allow designers to integrate peripheral circuits and processors in the same chip. Additionally, the PC-developed algorithm and C language program can be rapidly migrated to the Nios II processor to shorten the system development cycle [15].

Fig. 3. The experimental setup.

The proposed AFDSC algorithm is realized in the Nios II programming interface. The BLDC motor system offers high performance and simple operation from a compact driver and motor. The specification of the adopted BLDC motor system is manufactured by the Orientalmotor Company [16]. It should be emphasized the proposed AFDSC scheme does not need to know the system dynamics of the BLDC motor. For practical implementation, the controller parameters can be on-line tuned by the adaptive laws.

The proposed AFDSC system is applied to the BLDC motor. The control parameters are selected as $a_1 = b_1 = 2$, $a_2 = b_2 = 1$, $\eta_\alpha = 20$, and $\eta_m = \eta_\sigma = 0.002$. All the gains are chosen to achieve good transient control performance in the experiment considering the requirement of stability. The experimental results of the AFDSC system are depicted in Fig. 4. The tracking response is shown in Fig. 4(a) and the associated control effort is shown in Fig. 4(b), respectively. The experimental results show that the favorable tracking performance can be achieved after FWNN learning. Further, the trained AFDSC is applied to the BLDC motor system again. The experimental results of the trained AFDSC system are depicted in Fig. 5. The tracking response is shown in Fig. 5(a) and the associated control effort is shown in Fig. 5(b), respectively. It shows the proposed AFDSC scheme can achieve favorable control performance without occurring chattering phenomena.

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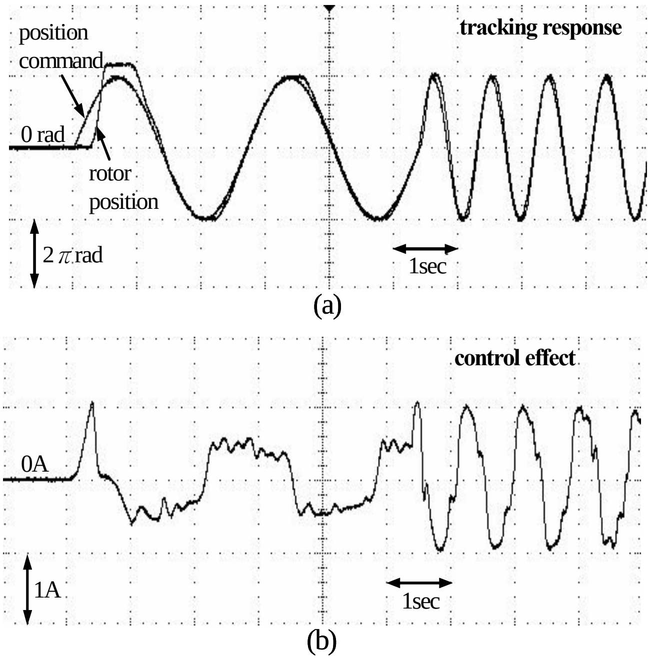

Fig. 4. Experimental results of the AFDSC system.

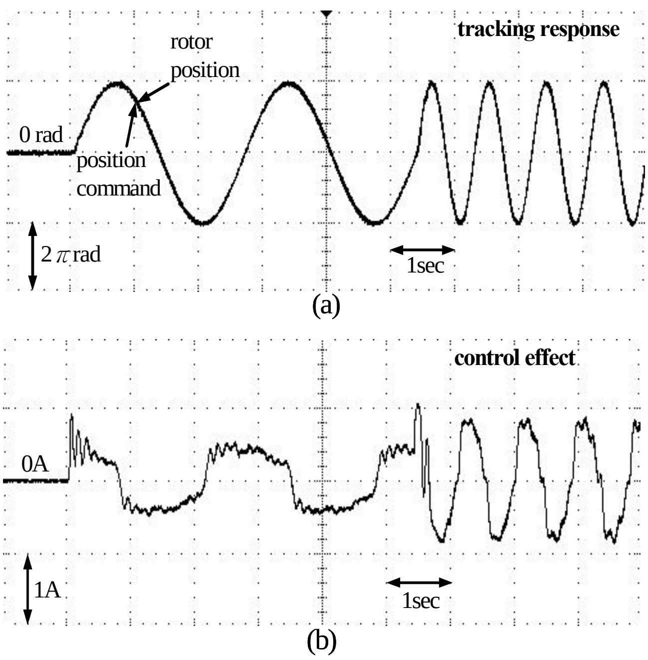

Fig. 5. Experimental results of the trained AFDSC system.

V. Conclusion

This paper proposes an adaptive fuzzy-neuro-wavelet dynamic sliding-mode control (AFDSC) using the dynamic sliding-mode approach to remove the chattering phenomenon. The proposed AFDSC system is composed of a neural controller and a switching compensator. The neural controller using a fuzzy wavelet neural network (FWNN) is the main controller, and the switching compensator is designed to eliminate the approximation error introduced by neural controller. The stability of the AFDSC is proven by Lyapunov function to adjust the controller parameters. Finally, the hardware implementation of the AFDSC scheme is developed on a field programmable gate array (FPGA) chip in a real-time mode. Some experimental results show the effectiveness of the proposed AFDSC system.

The main contributions of this paper are: (1) the successful applications of AFDSC to control a BLDC motor. The proposed AFDSC methodology can be easily extended to other motors; (2) the FPGA implementation consumes less power, in terms of core IC power consumption and especially in terms of the board-level power consumption, than the PC and DSP implementation.

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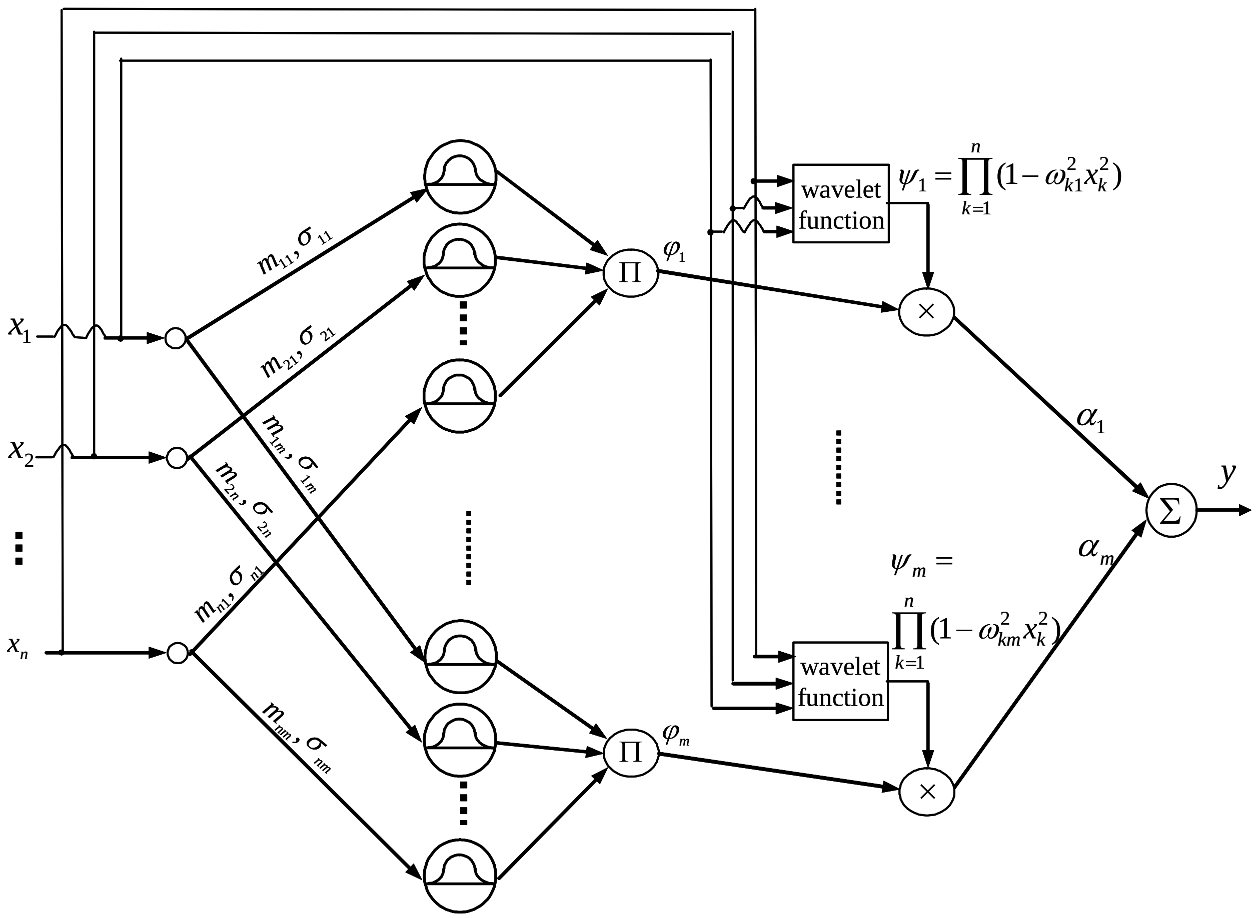

Fig. 1. The architecture of FWNN.

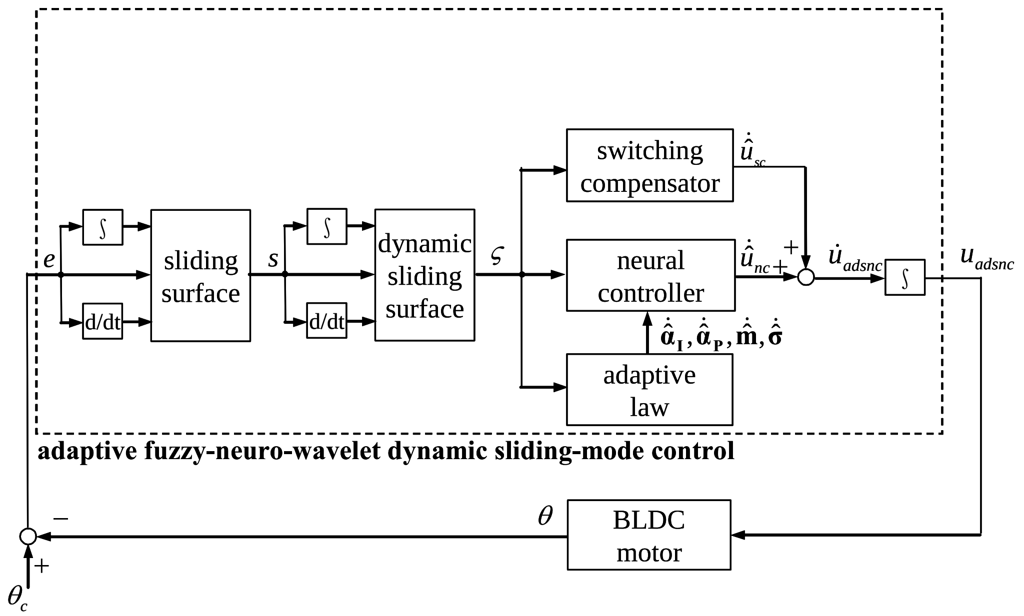

Fig. 2. The block diagram of the AFDSC system for a BLDCmotor.

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