VSC Perspective for Neurocontroller Tuning*

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Abstract. Compact representation of knowledge having strong internal interactions has become possible with the developments in neurocomputing and neural information processing. The field of neural networks has offered various solutions for complex problems, however, the problems associated with the learning performance has constituted a major drawback in terms of the realization performance and computational requirements. This paper discusses the use of variable structure systems theory in learning process. The objective is to incorporate the robustness of the approach into the training dynamics, and to ensure the stability in the adjustable parameter space. The results discussed demonstrate the fulfillment of the design specifications and display how the strength of a robust control scheme could be an integral part of a learning system. This paper discusses how Gaussian radial basis function neural networks could be utilized to drive a mechatronic system's behavior into a predefined sliding regime, and it is seen that the results are promising.

Keywords: Gaussian Radial Basis Function Networks, Sliding Mode Control.

1 Introduction

The innovations observed in the field of digital technology particularly in the last few decades have accelerated the analysis and interpretations of data collected from physical phenomena, and have made it possible to design and implement the systems based on the former work. Tools used for this purpose have been refined, and artificial neural networks, as one of the powerful tools for modeling and representation of complex mappings, have taken a central role. What make them so attractive have been their capability of representing inextricably intertwined dependencies in a large data set with a simple model, the learning and generalization ability, furthermore, to do all these with a certain degrees of fault tolerance.

When the applications of neural networks are visualized together with the process of refining the future performance, i.e. the process of learning, several important issues need to be addressed very carefully. These contain, but are not limited to the issues related to the parametric stability, generalization versus memorization, setting up the architectural degrees of freedom and so on.

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* This work was supported by TOBB Economics and Technology University, BAP Program, under contract no ETÜ-BAP-2006/04

S. Kollias et al. (Eds.): ICANN 2006, Part I, LNCS 4131, pp. 918 – 927, 2006.

The first important milestone in the area of training process is the discovery of Error Backpropagation (EBP) technique [1], which is also known as MIT rule or gradient descent in the literature. Since the EBP method concerns the first order partial derivatives of a cost function, the studies appeared later on have focused on the extraction of a better path to the minimum cost solution by exploiting the information contained in second order derivatives of the cost measure. Newton's method [2], Conjugate Gradient Algorithm [3] and Levenberg-Marquardt (LM) optimization technique [4] are the most prominent ones used frequently in the neural network applications. An inherent problem associated with all these schemes has been the sensitivity of the learning model to the high frequency components additively corrupting the training pairs. One method that has been discussed in the literature is due to Efe et al [5-6], which suggest a dynamic model for the training process and develop a stabilizing scheme by utilizing Variable Structure Systems (VSS) theory. VSS theory is a well-formulated framework for designing control systems particularly for plants having uncertainties in the representative models. The approach has extensively been used for tracking control of nonlinear systems and a good deal of VSS and intelligence integration have been discussed in [7-8] also with the name Variable Structure Control (VSC), which is a VSS theory based control scheme.

In what follows, we scrutinize the concept of VSS theory use in neurocomputing from systems and control engineering point of view. For this purpose, we shall use Gaussian Radial Basis Function Neural Networks (GRBFNNs) introduced in the second section. The third section is devoted to the extraction of an error critic, which is to be used in parameter tuning stage. In the fourth section, a simulation example is considered and the concluding remarks are presented at the end of the paper.

2 Gaussian Radial Basis Function Neural Networks (GRBFNN)

In the literature, GRBFNNs are generally considered as a smooth transition between Fuzzy Logic (FL) and NNs. Structurally, a GRBFNN is composed of receptive units (neurons) which act as the operators providing the information about the class to which the input signal belongs. If the aggregation method, number of receptive units in the hidden layer and the constant terms are equal to those of a Fuzzy Inference System (FIS), then there exists a functional equivalence between GRBFNN and FIS [9]. As illustrated in Fig. 1, the hidden neurons of a GRBFNN possess basis functions to characterize the partitions of the input space. Each neuron in the hidden layer provides a degree of membership value for the input pattern with respect to the basis vector of the receptive unit itself. The output layer is comprised of linear neurons. NN interpretation makes GRBFNN useful in incorporating the mathematical tractability, especially in the sense of propagating the error back through the network, while the FIS interpretation enables the incorporation of the expert knowledge into the training procedure. The latter is of particular importance in assigning the initial value of the

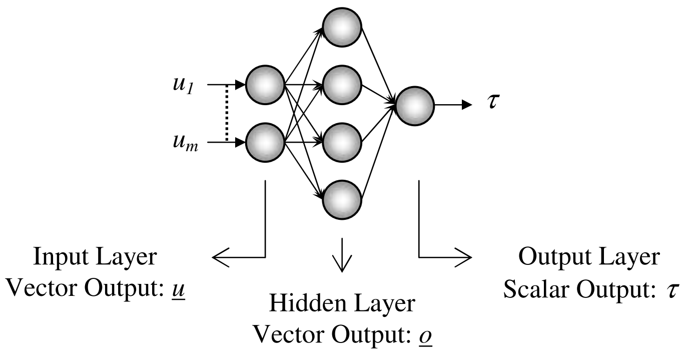

Fig. 1. Structure of a GRBFNN having m-input and single output

network's adjustable parameter vector to a vector that is to be sought iteratively. Expectedly, this results in faster convergence in parameter space.

Mathematically, $o_i=\Pi^m_{j=1}\Psi_{ij}(u_j)$ and the hidden layer activation function is the Gaussian curve described as $\Psi_{ij}(\underline{u})=\exp\{-(u_j-c_{ij})^2/\sigma_{ij}^2\}$, where c_{ij} and σ_{ij} stand for the center and the variance of the i^{th} neuron's activation function qualifying the j^{th} input variable. The output of the network is evaluated through the inner product of the adjustable weight vector denoted by $\underline{\phi}$ and the vector of hidden layer outputs, i.e. $\tau=\underline{\phi}^{\mathrm{T}}\underline{o}$. Clearly the adjustable parameter set of the structure is composed of $\{\underline{c}, \underline{\sigma}, \underline{\phi}\}$ triplet.

3 VSS Theory from a Learning-Strategic Point of View

The pioneering works due to Sanner and Slotine [10] and Sira-Ramirez and Colina-Morles [11] have demonstrated the first successful results in learning design with VSS theory. The latter introduced the concept of zero learning error level, which makes the design of switching manifold comprehensible for first order systems. Since the design of VSC involves a decision based on a two sided mechanism, the boundary of which is characterized by the switching manifold, the geometric location of the manifold for first order systems becomes a point in one dimensional space and is defined to be the zero level of learning [11]. Although a zero level is postulated conceptually, the achievement of which is a challenge unless there is a supervision providing the desired values of the neural network outputs. In [12], an appropriate measure relating the dynamics of the switching manifold and controller error is postulated.

In what follows, we briefly explain how an appropriate error measure for control error could be constructed, and demonstrate how this measure could be used for control applications. For this purpose, it is assumed that the system is in an ordinary feedback loop as illustrated in Fig. 2.

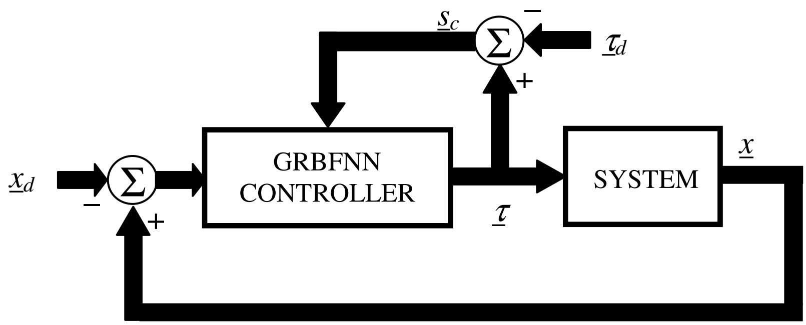

Fig. 2. Structure of the feedback control loop

3.1 Obtaining an Equivalent Control Error

Consider the system $\underline{\ddot{x}} = \underline{f}(\underline{x}, \underline{\dot{x}}) + b(\underline{x})\underline{\tau}$, where $(\underline{x}, \underline{\dot{x}})^{\mathrm{T}}$ is the state vector, $\underline{\tau}$ is the input vector and f and b are unknown continuous functions. If $\underline{x}_d$ is defined to be the vector of desired trajectories, one can describe the tracking error vector as $\underline{e}=\underline{x}-\underline{x}_d$ and construct the control signal that derives the system towards the prescribed sliding regime. The design is based on a two-sided switching mechanism, the argument of which is defined as $\underline{s}_p=\mathrm{d}\underline{e}/\mathrm{d}t+\Lambda\underline{e}$ with Λ being a positive definite diagonal matrix of appropriate dimensions. The aim is to ensure the negative definiteness of the Lyapunov function $V_p=\underline{s}_p^{\mathrm{T}}\underline{s}_p/2$. The control sequence can now be formulated as $\underline{\tau} = -b^{-1}(\underline{x})\left(\underline{f}(\underline{x}, \underline{\dot{x}}) + \Lambda\underline{\dot{e}} + \Xi\,\mathrm{sgn}(\underline{s}_p) - \underline{\ddot{x}}_d\right)$, where, Ξ is a positive definite diagonal matrix. The application of the well-known sliding control law above the system enforces $\underline{\dot{s}}_p = -\Xi\,\mathrm{sgn}(\underline{s}_p)$, which ensures the reaching to the hyperplane $\underline{s}_p=\underline{0}$.

Proposition: Let $\underline{\tau}_d$ be the vector of control signals that meets the performance specifications. If $\underline{s}_C$ is defined to be the vector of discrepancies between the target and evaluated values of the control vector, and if the controller parameters are adjusted such that the cost function $J=\underline{s}_C^{\mathrm{T}}\underline{s}_C/2$ is minimized, the tracking error vector is driven towards the switching manifold. Here, $\underline{s}_C$ is defined to be the error on the control signal and is computed as given in (1).

$$\underline{s}_C := \underline{\dot{s}}_p + \Xi\,\mathrm{sgn}(\underline{s}_p) = \underline{\tau} - \underline{\tau}_d \tag{1}$$

In reality, one does not know the numerical value of $\underline{\tau}_d$, however, within the context of discussed problem, the set of all control signals forcing the system towards the sliding manifold can be considered as the target control sequence, which minimizes $\underline{s}_C$. Practically, this means $\underline{\dot{s}}_p\underline{s}_p < 0$, i.e. all trajectories in the phase space tend to the sliding manifold and the ideal behavior thereafter takes place in the sliding subspace. An indirect implication of this is the fact that since $\underline{s}_C = \underline{\dot{s}}_p + \Xi\,\mathrm{sgn}(\underline{s}_p)=0$ is maintained, the parameters of the controller are not adjusted during the sliding regime. At this point, we dwell the numerical computation of this error measure. The obvious difficulty is the computation of the time derivative of $\underline{s}_p$. Our prior tests have proved that an approximate numerical differentiation works even with the noisy observations. Introducing a stable linear filter with numerator of order one in Laplace domain can suitably provide the information needed. The reason why we do not need the exact value of the derivative stems from the fact that the desired behavior is not unique. If a trajectory starting from an arbitrary initial point in the space tends to the sliding manifold then it is one of the desired trajectories, however, the selection of Ξ uniquely determines the way of approaching the sliding manifold. The information loss due to the derivative computation can be interpreted as a slight modification of the reaching dynamics characterized by $\dot{\underline{s}}_p = -\Xi\,\mathrm{sgn}(\underline{s}_p)$. The second question is on the selection of the diagonal positive definite matrix Ξ. If the entries increase in magnitude, the reaching phase of the control strategy produce large controls in magnitude and several hittings occur, however, the values close to zero result in slow reaching to the sliding manifold with relatively less number of hittings. The designer has to decide on what he/she pursues together with the physical reality regarding the plant under control. For example, for a cargo ship steering example, enforcing the convergence to a desired behavior in a few seconds would require unrealistically large-magnitude control activity, while for a direct drive robotic manipulator the response could reasonably be fast to fulfill the imposed task. Lastly, the infinite switching frequency of ideal sliding mode should be addressed. Clearly from $\dot{\underline{s}}_p = -\Xi\,\mathrm{sgn}(\underline{s}_p)$, one should notice that the enforced behavior ultimately converges to a practically impossible phenomenon. Since the right hand side of the equation is discontinuous in the vicinity of the origin, the near origin activity is an oscillation ideally at infinite frequency, called *chattering* in the terminology of sliding control. One approach to eliminate the adverse effects of chattering is to introduce a boundary layer by replacing the discontinuous sign function with a smooth approximate such as $\mathrm{sgn}(\alpha) \cong \alpha / \left(|\alpha| + \delta \right)$, where $\delta > 0$ is the parameter determining the accuracy of the approximation.

3.2 Issues of Parameter Tuning

The quantity described in (1) can be used in several ways. Assume that the system is under the feedback loop as illustrated in Fig. 2, and the tuning strategy is the EBP rule. Denoting $\underline{\phi}$ as the vector adjustable parameters of a neural network structure, the law enforces the following tuning mechanism:

$$\dot{\underline{\phi}} = -\eta \frac{\partial J}{\partial \underline{\phi}} = -\eta \sum_{j=1}^{n} s_{Cj} \frac{\partial \tau_j}{\partial \underline{\phi}} \qquad (2)$$

where $J = \sum_{j=1}^{n} s_{Cj}^2 / 2$ and η is the learning rate in the conventional sense. The similar reasoning can be postulated for other learning algorithms as well.

If the output of a neural network structure is linear in the adjustable parameter vector ($\underline{\phi}$), e.g. in the case of GRBFNN with only output weights adjustable, alternative mechanisms could be proposed. In (3), the tuning law proposed by Sira-Ramirez et al [11] has been given.

$$\underline{\dot{\phi}}_i = -\frac{\underline{\Omega}_i}{\underline{\Omega}_i^{\mathrm{T}}\underline{\Omega}_i} k_i \operatorname{sgn}\left(s_{C_i}\right) \tag{3}$$

In above, k_i is the uncertainty bound satisfying $k_i > B_{\phi_i} B_{\dot{\Omega}_i} + B_{\dot{\tau}_{id}}$ and $\underline{\Omega}_i$ is the vector excitation signals. Setting of k_i obviously requires the knowledge on the following bounds $\left\|\underline{\phi}_i\right\| \le B_{\phi_i}$, $\left\|\underline{\dot{\Omega}}_i\right\| \le B_{\dot{\Omega}_i}$ $\left\|\dot{\tau}_{id}\right\| \le B_{\dot{\tau}_{id}}$, which are typically unknown, therefore a compact k_i value is set by trial and error. For a detailed discussion on this adaptation law, one should refer to [7,11-12].

Alternatively, one might suggest the use of tuning strategy in (4), which is designed to ensure the negative semi-definiteness of the Lyapunov function in (5).

$$\underline{\dot{\phi}}_i = -k_i \left(\mu I + \rho \frac{\partial^2 V_{c_i}}{\partial \underline{\phi}_i \partial \underline{\phi}_i^T} \right)^{-1} \operatorname{sgn}\left(\frac{\partial V_{c_i}}{\partial \underline{\phi}_i} \right) \tag{4}$$

where $\mu > 0$ and $\rho > 0$ are the free design parameters determining the relative importance of the terms seen in (5), and $k_i > (\mu B_{\phi_i} + \rho B_{\Omega_i}) B_{\dot{\Omega}_i}$.

$$V = \mu V_{c_i} + \rho \frac{1}{2} \left\| \frac{\partial V_{c_i}}{\partial \underline{\phi}_i} \right\|^2 \text{ with } V_{c_i} = \frac{1}{2} s_{C_i}^2 \tag{5}$$

Clearly the above law and the Lyapunov function suggest that the parametric growth is penalized. Further discussion on this approach has been presented in [7]. For the strategy in (3), the zero error learning level is characterized by $s_{Ci} = 0$, while the latter uses an augmented switching manifold given as in (6). The law of (4) enforces a motion taking place in the vicinity of $s_{A_i} = 0$.

$$s_{A_i} = \begin{bmatrix} s_{c_i} \\ \dfrac{\partial V_{c_i}}{\partial \underline{\phi}_i} \end{bmatrix} \tag{6}$$

4 An Illustrative Example

To demonstrate the efficacy of the presented concept, the control of a 2 degrees of freedom direct drive arm is considered. The dynamics of the manipulator is described by the following vector differential equation.

$$\underline{\ddot{x}} = M^{-1}(\underline{x})\left(\underline{\tau} - \underline{f}_c - \underline{C}(\underline{x}, \underline{\dot{x}})\right) \tag{7}$$

where, $M(\underline{x})$, $\underline{C}(\underline{x}, \underline{\dot{x}})$, $\underline{\tau}$ and $\underline{f}_c$ stand for the state varying inertia matrix, the vector of Coriolis terms, the applied torque inputs and the Coulomb friction terms respectively.

The plant parameters are given in Table 1 in standard m-kg-s units. If the angular positions and angular velocities are described as the state variables of the system, four coupled and first order differential equations can define the model. In (8) and (9), the terms seen in (7) are given explicitly.

$$M(\underline{x}) = \begin{bmatrix} p_1 + 2p_3\cos(x_2) & p_2 + p_3\cos(x_2) \\ p_2 + p_3\cos(x_2) & p_2 \end{bmatrix} \tag{8}$$

$$V(\underline{x}, \underline{\dot{x}}) = \begin{bmatrix} -\dot{x}_2(2\dot{x}_1 + \dot{x}_2)p_3\sin(x_2) \\ \dot{x}_1^2 p_3 \sin(x_2) \end{bmatrix} \tag{9}$$

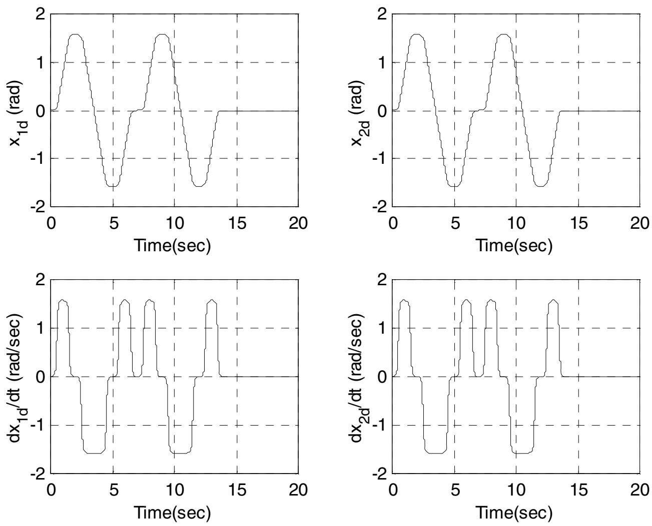

Fig. 3. Reference trajectories for base and elbow links

In the above equations, p_1 = 3.31655+0.18648M_p, p_2 = 0.1168+0.0576M_p and p_3 = 0.16295+0.08616M_p. Here M_p denotes the payload mass. The details of the plant model can be found in Direct Drive Manipulator R&D Package User Guide [13].

Since the dynamics of such a mechatronic system is modeled by nonlinear and coupled differential equations, precise output tracking becomes a difficult objective due to the strong interdependence between the variables involved. Additionally, the ambiguities on the friction related dynamics in the plant model and the varying payload conditions make the design much more complicated. Therefore the control methodology adopted must be capable of handling the difficulties stated.

As the controller, two GRBFNN structures having 2 inputs 9 hidden neurons and single output are used for each link, and only the weight parameters are adjusted with the tuning law of (3). Initially, the adjustable parameters have been set to zero and the

Table 1. 2D Manipulator parameters

Motor 1 Rotor Inertia	0.2670	Payload Mass (M_p)	2.0000
Arm 1 Inertia	0.3340	Arm 1 Length	0.3590
Motor 2 Rotor Inertia	0.0075	Arm 2 Length	0.2400
Motor 2 Stator Inertia	0.0400	Arm 1 CG Distance	0.1360
Arm 2 Inertia	0.0630	Arm 2 CG Distance	0.1020
Motor 1 Mass	73.000	Axis 1 Friction	4.9000
Arm 1 Mass	9.7800	Axis 2 Friction	1.6700
Motor 2 Mass	14.000	Torque Limit 1	245.00
Arm 2 Mass	4.4500	Torque Limit 2	39.200

uncertainty bounds have been set as k_1=10000 and k_2=1000. The simulation has been performed for 20 seconds, and the integration step size has been chosen as 2.5 ms. In response to the reference trajectories depicted in Fig. 3, the error trends shown in Fig. 4 are obtained. Clearly the suggested form of tuning and control strategy is capable of alleviating the nonzero initial errors together with a load of 2 kg grasped at t=2 sec, released at t=5 sec, and grasped again at t=9 sec and released at t=12 sec. This clearly introduces an abrupt change in the dynamics of the system and necessitates a robust controller to compensate the behavioral changes. Although not presented here, in the phase space, the behavior for each link is maintained on the loci characterized by λ=1 with tolerably small and convergent spikes in elbow velocity error.

The control inputs are depicted in the top row of Fig. 5, which reveals that the produced control signals sufficiently smooth and are of reasonable magnitudes. In the

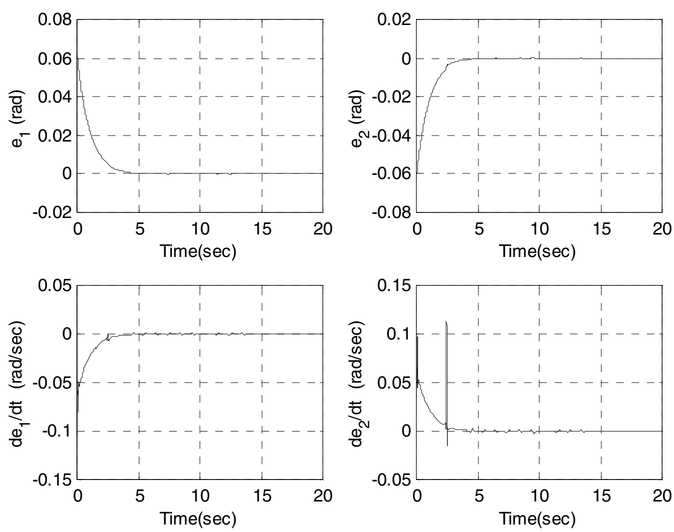

Fig. 4. State tracking errors

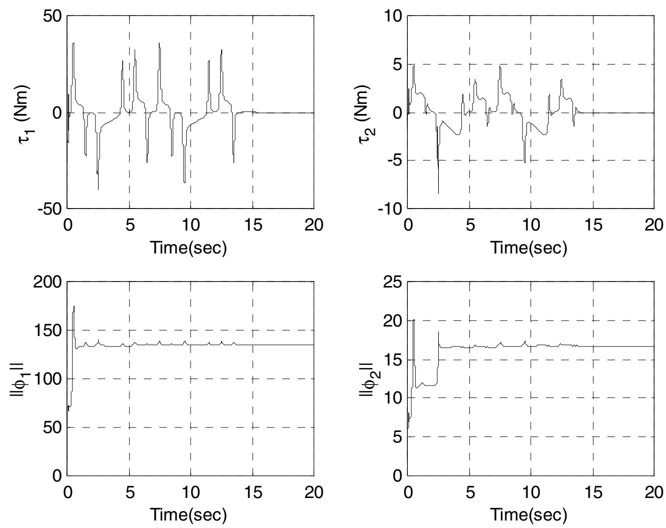

Fig. 5. Control inputs and parameter norms

bottom row of Fig. 5, the evolution of the Euclidean norm of the adjustable parameter vectors are shown. The obtained results clearly suggest that the tuning mechanism stops modifying the values of the parameters right after the sliding regime starts. Therefore, it can be claimed that the learning dynamics is internally stable for both controllers and the control system is robust against disturbances such as payload change as considered in this work.

5 Conclusions

This paper presents the use of VSS theory in training of GRBFNN type controllers. For this purpose, a novel error critic is discussed, and several tuning laws are presented. It has been exemplified that a tuning activity minimizing the proposed error measure drives the system under control into a prespecified sliding mode and results in robust and precise tracking. A robotic manipulator has been chosen as the test bed, and the internal stability of the adjustable parameter dynamics has been visualized. Briefly, the use of VSS theory for parameter tuning purposes introduces the robustness and invariance properties of the VSC technique, which results in some desirable features during the control cycle.

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