

Robust control using Analog Adaptive Resonance Theory

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Abstract - In many control system applications, the system designed must not only satisfy the damping and accuracy specifications, but the control must also yield performance that is robust to external disturbance and parameter variations. We have shown that feedback in conventional control systems has the inherent ability of reducing the effects of external disturbance and parameter variations. Unfortunately, robustness with the conventional feedback configuration is achieved only with a high loop gain, which is normally detrimental to stability. The design of intelligent, autonomous machines to perform tasks that are dull, repetitive, hazardous, or that require skill, strength, or dexterity beyond the capability of humans is the ultimate goal of robotics research. This paper prove the robust control using Analog Adaptive Resonance Theory(ART2) Algorithm about case study.

Key Words : robust, control, ART2, algorithm

1. INTRODUCTION

The design of intelligent, autonomous machines to perform tasks that are dull, repetitive, hazardous, or that require skill, strength, or dexterity beyond the capability of humans is the ultimate goal of robotics research. Examples of such tasks include manufacturing, excavation, construction, undersea, space, and planetary exploration, toxic waste cleanup, and robotic-assisted surgery[1]. An important class of robots are the manipulator arms, such as the robot arm.

These manipulators are used primarily in materials handling, welding, assembly, spray painting, grinding, deburring, and other manufacturing applications. Case study of this paper discusses the motion control of such manipulators. Robot manipulators are basically multi degree of freedom positioning devices. The robot, as the "plant to be controlled," is a multi-input/multi-output, highly coupled, nonlinear mechatronic system. The main challenges in the motion control problem are the complexity of the dynamics and uncertainties, both robot arm manipulator parametric and dynamic. Parametric uncertainties arise from imprecise knowledge of kinematic parameters and inertia parameters, while dynamic

uncertainties arise from joint and link flexibility, actuator dynamics, friction, sensor noise, and unknown environment dynamics. There are a number of excellent survey articles on the control of robot manipulators from an elementary view point [2], [3], [4]. We survey more recent and more advanced material that summarizes the work of many researchers from about 1985 to the present. Many of the ideas presented here are found in the papers reprinted in [5], which is recommended to the reader who wishes additional details.

2. DESIGN OF ROBUST CONTROL

In many control system applications, the system designed must not only satisfy the damping and accuracy specifications, but the control must also yield performance that is robust (insensitive) to external disturbance and parameter variations. We have shown that feedback in conventional control systems has the inherent ability of reducing the effects of external disturbance and parameter variations[6].

Unfortunately, robustness with the conventional feedback configuration is achieved only with a high loop gain, which is normally detrimental to stability. Let us consider the control system shown in Fig 1. The external disturbance is denoted by the signal $d(t)$, and we assume that the amplifier gain K is subject to variation during operation.

The input-output transfer function of the system when

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$d(t)=0$ is

$$M(s) = \frac{Y(s)}{R(s)} = \frac{KG_c(s)G_c(s)G_p(s)}{1+KG_c(s)G_p(s)} \quad (1)$$

and the disturbance-output transfer function when $r(t)=0$ is

$$T(s) = \frac{Y(s)}{D(s)} = \frac{1}{1+KG_c(s)G_p(s)} \quad (2)$$

In general, the design strategy is to select the controller $G_c(s)$ so that the output $y(t)$ is insensitive to the disturbance over the frequency range in which the latter is dominant, and the feed-forward controller $G_f(s)$ is designed to achieve the desired transfer function between the input $r(t)$ and the output $y(t)$. Let us define the sensitivity of $M(s)$ due to the variation of K as

$$S_K^M = \frac{\text{percent change in } M(s)}{\text{percent change in } K} = \frac{dM(s)/M(s)}{dK/K} \quad (3)$$

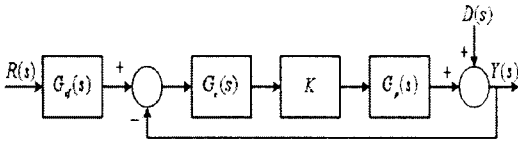


Fig 1. Control system with disturbance.

Then, for the system in Fig 1,

$$S_K^M = \frac{1}{1+KG_c(s)G_p(s)} \quad (4)$$

which is identical to (2). Thus the sensitivity function and the disturbance-output transfer function are identical, which means that disturbance suppression and robustness with respect to variations of K can be designed with the same control schemes.

3. ART2 NEURAL NETWORK

ART2 is a two-layer, nearest-neighbor classifier that stores an arbitrary number of analog spatial patterns $A_k = (a_1^k, \dots, a_n^k)$, $k=1, 2, \dots, m$ using competitive (gated decay LTM) learning. ART2 learns online, operates indiscrete or continuous time, where the n F_0 PEs correspond to A_k 's components and the p F_n PEs each represent a pattern class.

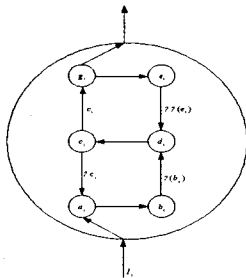


Fig. 2 ART Unit Model

Fig. 2 is an expanded view of the F_0 PE showing the six inter-PEs that are used for normalization of the analog patterns stored in LTM (the connections between F_0 and F_n) and the input patterns. Pattern normalization allows an equitable comparison to be made between the stored and input pattern.

The encoding procedure is outlined as follows:

1. Present an input pattern $A_k = (a_1^k, \dots, a_n^k)$ to the F_0 PEs.
2. Inside each F_0 PE the analog input pattern is normalized and fed through the $a_i \rightarrow b_i \rightarrow d_i \rightarrow c_i \rightarrow g_i$ inter-PE path, and sends the resultant signal through the F_0 to F_n LTM connections.
3. Each F_n competes with the others using Shunting Grossberg interactions until only one F_n PE remains active.
4. The winning F_n PE sends a top-down signal through its LTM connections, v_n back to F_0 .
5. The top-down signal is sent through the $g_i \rightarrow e_i \rightarrow d_i \rightarrow c_i$ inter-PE path resulting in a possibly new c_i signal.
6. The combined normalized top-down LTM/bottom-up input signal at c_i is compared with the top-down stored signal S_i .
7. If the difference between these two activations C_i and S_i exceeds a value determined by the vigilance parameter then the winning F_n PE does not represent the proper class for A_k and it is removed from the set of allowable F_n winners. Control branches at this point in one of two directions:
 - a. If there are still F_n PEs remaining in the set of allowable winners, go to step 2.
 - b. If there are no remaining F_n PEs in the set of allowable winners, recruit an uncommitted F_n PE and encode the normalized input onto this's connections.
8. If the difference between the two activations meets the criterion established by the vigilance parameter, then the F_n PE is determined to be the proper class for the for the input pattern A_k and the input pattern is merged onto the weights with the stored pattern. We will call this match between the input and stored patterns resonance, and we shall call the length of time that the match occurs the resonance period.

4. CASE STUDY

4.1 Experiment

Define z_0, z_1, z_2, z_3, z_4 , determine x_0, x_1, x_2, x_3, x_4 , determine y_i by RHR. This robot-arm has four motor and four-polynomial. Fig 3 is Robot-arm system and Equation (5) is polynomial of robot-arm.

$$G(s) = \frac{K(s^2 + 2s + 4)}{s(s+4)(s+6)(s^2 + 1.4s + 1)} \quad (5)$$

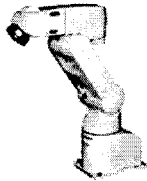


Fig 3. Robot-arm system

We described a neural network architecture that can solve classical robot-arm system problem. The algorithm is based on the logarithmic barrier function approach to robot-arm system problem. In other to solve the basic dynamics of these networks, we simulated robot-arm system problem using the differential-equation approach. And this paper proved robust Control using ART2 Algorithm of robot-arm system about disturbance.

4.2 Result

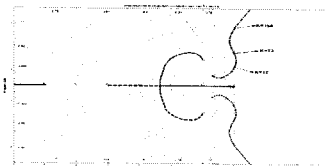


Fig 4. Root-Locus plot of conditionally stable system

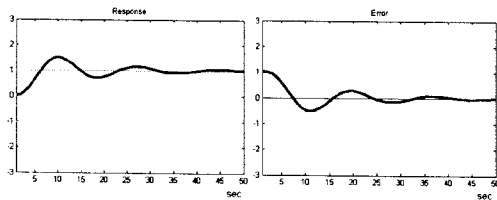


Fig 5. System response and error using ABAM

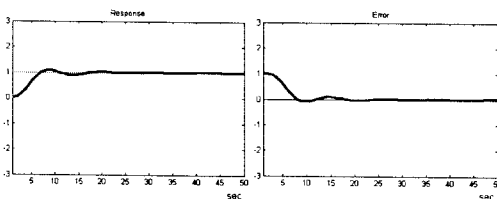


Fig 6. System response and error using ART2

In practice, conditionally stable systems are not desirable. Conditional stability is dangerous but does occur in certain systems, in particular, a system that has an unstable feed-forward path. Such an unstable feed-forward path may occur if the system has a minor loop. It is advisable to avoid such conditional stability since, if the gain drops beyond the critical value for any reason, the system becomes unstable. Note that the addition of a proper compensating network will eliminate conditional stability. An addition of a zero will cause the root loci to bend to the left. Hence conditional stability may be eliminated by adding proper compensation.

5. CONCLUSION

TABLE 1 is comparison error rate and overshoot of each method.

TABLE 1

Method	ABAM	ART2
Overshoot	0.527	0.161
Error rate	0.261	0.072

In this paper, we described a neural network architecture that can solve classical robot-arm systemproblem with a massively parallel algorithm. The algorithm is based on the logarithmic barrier function approach to robot-arm system problem. In other to solve the basic dynamics of these networks, we simulated robot-arm systemproblem using the ART2 algorithm. As you see the Fig 4-6 and TABLE 1 about case study, this paper demonstrated robot-arm system problem used ART2 algorithm of robot-arm system about disturbance.

Reference

- [1] Asada, H. and Slotine, J-J. E., Robot Analysis and Control, John Wiley & Sons, Inc., New York, 1986.
- [2] Dorf, R. C., Ed., International Encyclopedia of Robotics: Applications and Automation, John Wiley & Sons, Inc., 1988.
- [3] Luh, J.Y.S., Conventional controller design for industrial robots: a tutorial, IEEE Trans. Syst.,Man, Cybern., 13(3), 298-316, May/June 1983.
- [4] Nof, S.Y.,Ed, Handbook of Industrial Robotics, John Wiley &Sons, Inc., New York, 1985.
- [5] Spong, M.W., Lewis, F., and Abdallah, C., Robot Control: Dynamics, Motion Planning, and Analysis, IEEE Press, 1992.
- [6] Benjamin C. Kuo, Automatic Control Systems, Prentice Hall, 778-779, 1995.