Article ID: 1000 - 8152(2001)06 - 0897 - 05

Robust Neural-Network Compensating Control for Robot Manipulator Based on Computed Torque Control *

BAI Ping
(Department of Electrical Engineering and Information Science, University of Science and Technology of China · Hefei, 230026, P. R. China)
(Hefei Institute of Intelligent Machines, Chinese Academy of Sciences · Hefei, 230031, P. R. China)
FANG Tingjian and GE Yunjian
(Hefei Institute of Intelligent Machines, Chinese Academy of Sciences · Hefei, 230031, P. R. China)

Abstract: This paper proposes a new controller design approach for trajectory tracking of robot manipulator with uncertainties. The proposed controller is based on the computed torque control structure, and incorporates a compensator, which is realized by Functional Link Neural Network, and a robustifying term. In addition, when neural newtork reconstruction error is not uniformly bounded, an adaptive robustifying term is designed. It is shown that all the signals in the closed-loop system are uniformly ultimately bounded. Compared with other approaches, no joint acceleration measurement and exactly known inertia matrix are required. Both theory and simulation results show the effectiveness of the proposed controller.

Key words: robot manipulator; computed torque control; neural network; robust; adaptive
Document code: A

基于计算转矩控制结构的机械手鲁棒神经网络补偿控制

白 萍　　方廷健　葛运建
(中国科学技术大学电子工程与信息科学系·合肥,230026)　(中国科学院合肥智能机械研究所·合肥,230031)
(中国科学院合肥智能机械研究所·合肥,230031)

摘要: 提出了一种新的不确定性机器人跟踪控制策略.文中基于计算转矩控制结构,采用了函数链网络实现一个神经网络补偿器,并叠加一个鲁棒控制项,以补偿模型的不确定性部分.另外,还考虑了神经网络逼近误差非一致有界的情形,设计了自适应的鲁棒控制项.算法可保证跟踪误差及神经网络权估计最终一致有界.与其它有关基于计算转矩控制的方法相比,该算法既不需要测量关节角加速度,也不要求惯性矩阵已知.理论和仿真均证明了算法的可靠性和有效性.

关键词: 机械手; 计算转矩控制; 神经网络; 鲁棒; 自适应

1 Introduction

Various versions of adaptive computed torque control have been developed in literature for motion control of robot manipulators with uncertainties. The interested reader may refer to Ortega and Spong[1] for overview. However, all of these control laws have more or less drawbacks, such as the requirements on measurement of the joint acceleration or the boundedness of the inverse of the estimated inertia matrix.

Recently, there has been an increasing interest in utilizing neural networks (NN) to construct control algorithms for robot system. Feng[2] presented a control scheme that takes advantage of simplicity of the computed torque methods, and incorporates a compensating controller to achieve high tracking performance. The compensating controller is realized by using a switch-type structure and an RBF NN. But joint accelerations are still required to be measurable, and also switch-type control brings about the chattering problem in control signal. Another computed torque control scheme with a neuro-compensator was presented in Tan[3]. Nevertheless, the inertia matrix of robot was assumed exactly known in the algorithm. As the inertia parameters of robot manipulators are usually uncertain in most cases, this assumption has not been justified.

In this paper, a robust adaptive computed torque con-

* Foundation item: supported by Natural Science Foundation of China (60175027)
Received date: 2000 - 07 - 17; Revised date: 2001 - 02 - 14.

trol scheme using NN for robot trajectory tracking is proposed. Our method does not require the robot dynamics to be exactly known. Moreover, compared with the approaches in literature, no joint acceleration measurement and exactly known inertia matrix are required in it. Based on the computed torque method, this scheme incorporates a functional link neural network (FLNN) as compensating structure, which is trained on-line to identify the robot modeling error and a robustifying term. The algorithm can effectively attenuate the uncertainties of robot dynamics and guarantee the uniformly ultimately bounded (UUB) stability of tracking errors and NN weights. In addition, in the case where the NN reconstruction error is not uniformly bounded by a constant, we facilitate the properties of rigid robot dynamics and design an adaptive robustifying term to eliminate the NN reconstruction error and uncertainties.

2 Problem formulation

The dynamics of an n-link robot manipulator can be written as

$$M(q)\ddot{q} + H(q,\dot{q}) + \tau_d = \tau, \qquad (1)$$

with $q \in \mathbb{R}^n$ the vector of joint displacements, $M(q) \in \mathbb{R}^{n\times n}$ the symmetric positive definite manipulator inertia matrix, $H(q,\dot{q}) \in \mathbb{R}^n$ the vector of centripetal, Coriolis and gravitational torques. External disturbances are denoted by τ_d and the control input torque is τ.

If the robot modeling is perfect and there are no external disturbances, then according to the computed torque method, the robot controller should be chosen as

$$\tau = M(q)(\ddot{q}_d - k_v\dot{e} - k_p e) + H(q,\dot{q}) + \tau_d, \qquad (2)$$

which leads to the closed loop system expressed as

$$\ddot{e} + k_v\dot{e} + k_p e = 0, \qquad (3)$$

where

$$e = q - q_d,$$

and q_d is the desired joint position, k_v and k_p are constant design matrices to specify the desired transient performance of the closed loop system.

However, the perfect robot model is difficult to obtain and the external disturbances are always present in practice. Usually only a nominal model of the robot could be obtained. It is supposed that the nominal model is denoted by $M_0(q)$ and $H_0(q,\dot{q})$. Based on the nominal model, the computed torque controller is designed as

$$\tau = M_0(q)(\ddot{q}_d - k_v\dot{e} - k_p e) + H_0(q,\dot{q}), \qquad (4)$$

then, by substituting (4) into (1), we can obtain the following closed loop equations

$$\ddot{e} + k_v\dot{e} + k_p e =$$
$$M^{-1}[\Delta M(\ddot{q}_d - k_v\dot{e} - k_p e) + \Delta H - \tau_d], \qquad (5)$$

denoting $\Delta M = M_0 - M, \Delta H = H_0 - H$. It can be clearly seen that imperfect modeling of the robots will lead to degradation of the robot tracking performance. In some cases, the robot system could become unstable.

Let

$$x = [e \quad \dot{e}]^{\mathrm{T}},$$
$$f(x) = M^{-1}[\Delta M\ddot{q}_d - k_v\dot{e} - k_p e) + \Delta H - \tau_d].$$

As nonlinear function of the state variable $f(x)$ includes uncertainties of the robot dynamics, it is unknown a priori. Our objective is to design a compensating controller to eliminate the uncertainties, so as to to ensure the system stability and to improve the robot tracking performance. Due to its great approximation ability, PLNN will be used in this paper to identify the function $f(x)$.

3 Neural network controller design

Figure 1 depicts a functional link neural network (FLNN) which can be considered as a 2-layer feedforward neural network with input pocessing elements. It has a net output given by

$$y = W^{\mathrm{T}}\phi(p), \qquad (6)$$

where $W \in \mathbb{R}^{N\times m}$ is the hidden-to-output layer interconnection weights, $\phi(\cdot) \in \mathbb{R}^N$ is the activation function of hidden layer, $p \in \mathbb{R}^N$, which can be obtained by processing the net input $x \in \mathbb{R}^n$, is the input vector to hidden layer. Notice that the threshold values θ are considered. They are incorporated into weight matrices W and $\phi(p)$.

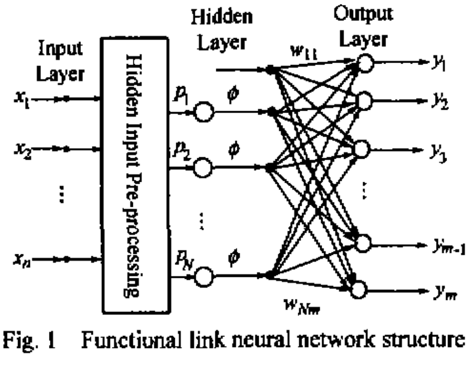

Fig. 1 Functional link neural network structure

Let S be a compact simply connected set of $\mathbb{R}^n$. With map $f: S \to \mathbb{R}^m$, define $C^m(S)$ the space such that f is continuous. A general nonlinear function $f(x) \in C^m(S)$ *can be approximated by an FLNN as*

$$f(x) = W^{\mathrm{T}}\phi(p) + \varepsilon(x). \qquad (7)$$

with $\varepsilon(x)$ an NN functional reconstruction error vector.

The ability of FLNN to approximate continuous functions has been widely studied[4]. If $\phi(\cdot)$ provides a basis, then for any function $f(x) \in C^m(S)$ and $\varepsilon_N > 0$ there exist finite N (the number of basis functions) and constant "ideal" weights so that (7) holds with $\|\varepsilon\| \leqslant \varepsilon_N$. Typical examples for basis $\phi(\cdot)$ are sigmoid and radial basis functions. The issue of selecting the number of basis functions N for a given $S \subset \mathbb{R}^n$ and ε_N, is a topic of current research.

Based on the computed torque method, and using FLNN to design compensator, the new control law is as follows

$$\tau = M_0(q)(\ddot{q}_d - k_v\dot{e} - k_p e) + H_0(q,\dot{q}) - \hat{f} + u_c, \qquad (8)$$

with $\hat{f} = \hat{W}^{\mathrm{T}}\phi$. $\hat{W}$ are the current values of the NN weights as provided by the tuning algorithm. u_c is a robustifying term to be defined shortly.

This control law leads to the closed loop system expressed in state-space form as

$$\dot{x} = Ax + B(\widetilde{W}^{\mathrm{T}}\phi + \varepsilon) + B(I - M^{-1})\hat{W}^{\mathrm{T}}\phi + BM^{-1}u_c. \qquad (9)$$

with $A = \begin{bmatrix} 0 & I \\ -k_p I & -k_v I \end{bmatrix}$, $B = \begin{bmatrix} 0 \\ I \end{bmatrix}$; $\widetilde{W} = W - \hat{W}$ the weight estimation errors.

As one can see that there is an unknown term $B(I - M^{-1})\hat{W}^{\mathrm{T}}\phi$ in (9) because inertia matrix M is usually unknown. The role of the robustifying term u_c is to suppress the effect of this signal. The form of u_c is chosen to be

$$u_c = -\frac{1}{m}\cdot\frac{c_0\|\hat{W}^{\mathrm{T}}\phi\|^2}{\|x^{\mathrm{T}}PB\|\cdot\|\hat{W}^{\mathrm{T}}\phi\| + v}B^{\mathrm{T}}Px, \qquad (10)$$

where the matrix P is the unique symmetric positive definite solution to the following Lyapunov equation $A^{\mathrm{T}}P + PA = -Q$ for a given symmetric, positive definite Q, and $v > 0$ is a small constant. c_0, m are defined as follows respectively

$$c_0 \geqslant \|I - M^{-1}\|, \quad m = \lambda_{\min}(M^{-1}), \qquad (11)$$

$\lambda_{\min}(\cdot)$ and $\lambda_{\max}(\cdot)$ denote the minimum eigenvalue and the maximum eigenvalue of a matrix respectively. The norm of a matrix is defined as Frobenius norm.

Theorem 1 For the robot system described by (1), let the desired trajectory $q_d, \dot{q}_d, \ddot{q}_d$ be bounded and the NN functional reconstruction error bound be constant. Take the control input given by (8), (10) and weight tuning provided by

$$\dot{\hat{W}} = F\phi x^{\mathrm{T}}PB - \kappa F\hat{W}, \qquad (12)$$

where F is any constant, symmetric, positive definite matrix and $\kappa > 0$. Then the tracking error $x(t)$ and NN weight estimates $\hat{W}$ are UUB.

Proof Consider the following Lyapunov function candidate

$$V = \frac{1}{2}x^{\mathrm{T}}Px + \frac{1}{2}\mathrm{tr}(\widetilde{W}^{\mathrm{T}}F^{-1}\widetilde{W}), \qquad (13)$$

which satisfies

$$\frac{1}{2}[\lambda_{\min}(P)\|x\|^2 + \lambda_{\min}(F^{-1})\|\widetilde{W}\|^2] \leqslant V \leqslant \frac{1}{2}[\lambda_{\max}(P)\|x\|^2 + \lambda_{\max}(F^{-1})\|\widetilde{W}\|^2]. \qquad (14)$$

Differentiating (13), we have

$$\dot{V} = -\frac{1}{2}x^{\mathrm{T}}Qx + x^{\mathrm{T}}PB(\widetilde{W}^{\mathrm{T}}\phi + \varepsilon) + x^{\mathrm{T}}PB(I - M^{-1})\hat{W}^{\mathrm{T}}\phi + x^{\mathrm{T}}PBM^{-1}u_c + \mathrm{tr}(\dot{\widetilde{W}}\,F^{-1}\widetilde{W}^{\mathrm{T}}). \qquad (15)$$

Using (10) and (12), we can further have

$$\dot{V} \leqslant -\frac{1}{2}x^{\mathrm{T}}Qx + \kappa\cdot\mathrm{tr}(\widetilde{W}^{\mathrm{T}}\hat{W}) + \|x\|\cdot\|PB\|\varepsilon_N + vc_0. \qquad (16)$$

Since

$$\mathrm{tr}(\widetilde{W}^{\mathrm{T}}\hat{W}) = 0.5[-\mathrm{tr}(\widetilde{W}^{\mathrm{T}}\widetilde{W}) - \mathrm{tr}(\hat{W}^{\mathrm{T}}\hat{W}) + \mathrm{tr}(W^{\mathrm{T}}W)],$$

there results

$$\dot{V} \leqslant -0.5(\lambda_{\min}(Q) - 1)\|x\|^2 - 0.5\kappa\,\mathrm{tr}(\widetilde{W}^{\mathrm{T}}\widetilde{W}) + \delta, \qquad (17)$$

where

$$\delta = 0.5\kappa\,\mathrm{tr}(W^{\mathrm{T}}W) + 0.5\|PB\|^2\varepsilon_N^2 + vc_0. \qquad (18)$$

Let

$$\lambda = \min\left\{\frac{\lambda_{\min}(Q) - 1}{\lambda_{\max}(P)}, \frac{\kappa}{\lambda_{\max}(F^{-1})}\right\},$$

we can rewrite (17) as

$$\dot{V} \leqslant -\lambda V + \delta. \qquad (19)$$

Note that,

$$V(t) \leqslant \frac{\delta}{\lambda} + \left(V(0) - \frac{\delta}{\lambda}\right)e^{-\lambda t}, \qquad (20)$$

from (20) and (14), it can be shown that $\|x\|$ and $\|W\|$ are UUB.

Remark According to the above proof process, the tracking error may be made as small as desired by properly choosing gain matrices k_p, k_v, decreasing the values of κ and $\lambda_{\max}(F)$.

Theorem 1 Assumes that the NN reconstruction error is uniformly bounded by a known value over the entire system operational region. With the support of the approximate theory of multilayer NN, such an error boundary can be made arbitrarily small, provided that certain conditions (e.g., sufficiently large number of neurons, sufficient smoothness of function of approximated function, etc.) are satisfied. However, in reality, one can only use a network with a finite number of neurons and that the nonlinear function being reconstruted may not be smooth enough. Thus, the approximation capabilities of the network can be guaranteed only on a subset of the whole plant state space. In other words, during the system operation, the reconstruction error is sometimes bounded by a constant, but at other times its magnitude may not necessarily be confined by that constant. Therefore the next result is meant to address the case where the NN reconstruction error is not uniformly bounded by a constant. In our development, we will facilitate the properties of rigid robot dynamic model to formulate the "magnitude" of ε, which allows the n-dimensional function to be "funneled" into a scalar nonlinear function. From (7), we have

$$\|\varepsilon\| \leqslant \|f(x) - W^{\mathrm{T}}\phi\|. \tag{21}$$

Assume the external disturbance is as follows

$$\|\tau_d\| \leqslant d_0 + d_1\|q\| + d_2\|\dot q\| + d_3\|q\|^2 + d_4\|\dot q\|^2, \tag{22}$$

with $d_i > 0$ (i = 0, 1, 2, 3, 4) are constant. Based on [6],

$$\|f(x)\| \leqslant \eta = \delta_1 + \delta_2\|x\| + \delta_3\|x\|^2, \tag{23}$$

where $\delta_i (i = 1,2,3)$ are the limit parameters of uncertainties of robot dynamics. Thus

$$\|\varepsilon\| \leqslant \eta + \|W\| \cdot \|\phi\|. \tag{24}$$

The control law of the robustifying term u_c is modified as

$$u_c = -\frac{1}{m}\frac{|\hat\Delta^{\mathrm{T}}\Psi|^2}{\|B^{\mathrm{T}}Px\|\hat\Delta^{\mathrm{T}}\Psi + v}B^{\mathrm{T}}Px, \tag{25}$$

where $\Delta = [\delta_1 \quad \delta_2 \quad \delta_3 \quad \|W\| \quad c_0]$, $\hat\Delta$ is the estimate of Δ, $\tilde\Delta = \Delta - \hat\Delta$ is the estimation error; $\Psi = [1 \quad \|x\| \quad \|x\|^2 \quad \|\phi\| \quad \|\hat W^{\mathrm{T}}\phi\|]^{\mathrm{T}}$. Therefore we have the following result:

Theorem 2 For the robot system described by (1), let the desired trajectory $q_d, \dot q_d, \ddot q_d$ be bounded. Take the control input be given by (8), (25) and weight tuning provided by

$$\dot{\hat W} = F\phi x^{\mathrm{T}}PB - \kappa_1 F\hat W, \tag{26}$$

the update law of $\hat\Delta$ is chosen as

$$\dot{\hat\Delta} = \Gamma \cdot \|x^{\mathrm{T}}PB\|\Psi - \kappa_2\Gamma\hat\Delta, \tag{27}$$

where Γ is any constant symmetric, positive definite matrix, and $\kappa > 0$. Then the tracking error $x(t)$ and NN weight estimates $\hat W$, parameter estimates $\hat\Delta$ are UUB.

Proof Define the Lyapunov function candidate

$$V = \frac{1}{2}x^{\mathrm{T}}Px + \frac{1}{2}\mathrm{tr}(\tilde W^{\mathrm{T}}F^{-1}\tilde W) + \frac{1}{2}\tilde\Delta^{\mathrm{T}}\Gamma^{-1}\tilde\Delta. \tag{28}$$

Differentiating (28) and using (26) yields

$$\dot V \leqslant -\frac{1}{2}x^{\mathrm{T}}Qx + \|x^{\mathrm{T}}PB\| \cdot \|\varepsilon + (I - M^{-1})\hat W^{\mathrm{T}}\phi\| + x^{\mathrm{T}}PBM^{-1}u_c + \tilde\Delta^{\mathrm{T}}\Gamma^{-1}\dot{\tilde\Delta} + \kappa_1\mathrm{tr}(\tilde W^{\mathrm{T}}\hat W). \tag{29}$$

Since

$$\|\varepsilon + (M^{-1} - I)\hat W^{\mathrm{T}}\phi\| \leqslant \eta + \|W\| \cdot \|\phi\| + c_0 \cdot \|\hat W^{\mathrm{T}}\phi\| = \Delta^{\mathrm{T}}\Psi, \tag{30}$$

therefor

$$\dot V \leqslant -\frac{1}{2}x^{\mathrm{T}}Qx + \|x^{\mathrm{T}}PB\| \cdot \tilde\Delta^{\mathrm{T}}\Psi + x^{\mathrm{T}}PBM^{-1}u_c + \tilde\Delta^{\mathrm{T}}\Gamma^{-1}\dot{\tilde\Delta}. \tag{31}$$

Substituting (27) into (31), we can proceed the same proof as Theorem 1. It can be shown that $x(t)$ and $\hat W$, $\hat\Delta$ are UUB.

4 Simulation

In this section, a simulation study is conducted to demonstrate the performance of our algorithms. A simple two degrees of freedom manipulator was used in the simulation. The model for this robot manipulator can be described as

$$\begin{bmatrix} \alpha_1 + 2\alpha_4\cos q_2 & \alpha_3 + \alpha_4\cos q_2 \\ \alpha_3 + \alpha_4\cos q_2 & \alpha_2 \end{bmatrix}\begin{bmatrix}\ddot q_1 \\ \ddot q_2\end{bmatrix} + \begin{bmatrix} -\alpha_4\dot q_2\sin q_2 & -\alpha_4(\dot q_1 + \dot q_2)\sin q_2 \\ \alpha_4\dot q_1\sin q_2 & 0\end{bmatrix}\begin{bmatrix}\dot q_1 \\ \dot q_2\end{bmatrix} + \begin{bmatrix}\alpha_5 g\cos q_1 + \alpha_6 g\cos(q_1 + q_2) \\ \alpha_6 g\cos(q_1 + q_2)\end{bmatrix} = \begin{bmatrix}\tau_1 \\ \tau_2\end{bmatrix},$$

with $\alpha_i (i = 1,2,\cdots,6)$ the model parameters. The external disturbance is supposed to be $\tau_d = [\sin^2(\pi t) \quad 2\cos(0.5\pi t)]$. The desired joint trajectory is described by $q_d(t) = [\cos t \quad \sin t]^{\mathrm{T}}$.

The initial state is $x(0) = [0.3 \quad -0.2 \quad 0.1 \quad 0.2]$. The gains are chosen as $k_p = 4.0, k_v = 16.0$. The inputs to hidden layer of FLNN are given by

$$p = [1 \; e^{\mathrm{T}} \; \dot{e}^{\mathrm{T}} \; \zeta^{\mathrm{T}} \; \| q_1 \| \; \| q_2 \| \,],$$

with $\zeta = \ddot{q}_d - k_v \dot{e} - k_p e$. There are 9 hidden neurons and 2 output neurons. The hidden neuron activation functions are $\phi(z) = 1/(1+\exp(-z))$. The learning parameters in the weight tuning law are $F = \mathrm{diag}\{20\}_{9\times 9}$, $\kappa = 0.1, v = 0.05$. The joint tracking performance is shown in Fig.2 and Fig. 3.

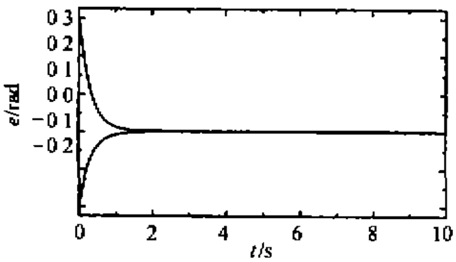

Fig. 2 Position tracking errors of the two joints

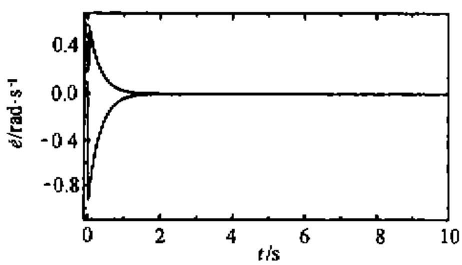

Fig. 3 Velocity tracking errors of the two joints both tracking errors go to small value

It has been clearly observed from the above figues that, the proposed NN compensating controller effectively attenuate the effects of uncertainties of robot dynamics and the tracking errors converge to small values, although there exist big modeling errors.

5 Conclusion

We have presented a novel robust NN compensating control method to the motion control of robot manipulators. The proposed scheme consists of well-known computed torque controller, which is based on the known nominal robot dynamics model, and NN-based compensating controller, and robustifying term. In addition, when neural network reconstruction error is not uniformly bounded, the adaptive robustifying term is designated. The weight of NN is trained on-line based on Lyapunov theory and all the signals in the closed-loop system are thus all guaranteed to be UUB. The simulation results have demonstrated the efficiency of the proposed scheme.

References

[1] Ortega R and Spong M W. Adaptive motion control of rigid robots: a tutorial [J]. Automatica, 1989,25(6):877 – 888

[2] Feng G. A new stable tracking control scheme for robotic manipulators [J]. IEEE Trans. Systems, Man, Cybernetics-Part B: Cybernetics, 1997,27(3):510 – 516

[3] Tan z and Jiang h m. Computed-torque control scheme for robot manipulators with a neuro-compensator [J]. Jiqiren, 1998,21(2):104 – 109

[4] Lewis F L, Liu K and Yesildirek A. Neural net robot controller with guaranteed tracking performacnce [J]. IEEE Trans. Neural Networks, 1995,6(3):703 – 715

[5] Song Y D. Neuro-adaptive control with application to robotic systems [J]. Journal of Robotic Systems, 1997,14(6):433 – 447

[6] Craig J J. Adaptive Control of Mechanical Manipulators [M]. New York: Addison-Wesley, 1988

本文作者简介

白 萍 1970年生.1998年于南京理工大学获硕士学位.现为中国科技大学电子工程与信息科学系博士研究生.研究方向为机器人神经网络控制,鲁棒控制等.

方廷健 1939年生.中国科学院合肥智能机械研究所研究员,中国科技大学兼职博士生导师.主要研究方向为智能控制,模式识别等.

葛运建 1947年生.法国里昂国家应用科学学院博士.现为中国科学院合肥智能机械研究所研究员,博士生导师.主要研究方向为信号与信息处理,智能机器人传感器等.