Adaptive Augmented Kalman Modeling for Embedded Autonomous Robot Systems under Wireless Sensor Network

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Abstract

This paper presents a Kalman filter based modeling algorithm for autonomous robots. State of the robot systems is measured by using embedded sensors and then carried to a host computer via ubiquitous sensor network (USN). We settle a linear state space motion equation for unknown system dynamics and modify a popular Kalman filter algorithm in deriving suitable parameter estimation mechanism. We conduct real-time experiment to test our proposed modeling algorithm where velocity state of the constructed robot is used as system observation.

1. Introduction

Recently, communication network-based monitoring, diagnostic and control systems have been the focus of many industrial applications. These systems were motivated in part by the increase in wireless communication applications. Their major advantage is that even complex systems can be easily implemented with more reliability and efficiency. Furthermore, the ubiquitous sensor network (USN) provides a popular realization of network-based systems [1]-[5].

An important issue in implementing network-based dynamic systems is time delays. Since time delays cause deterioration in system stability or performance, a more efficient system configuration to overcome their effects is required [6]-[10]. In addition, mathematical modeling of network-based systems must account for the effects of time delays to provide reliable estimates of system parameters. Unfortunately, most existing algorithms for USN modeling typically neglect time delays.

This paper presents a novel modeling algorithm for autonomous robot systems under USN configuration based on Kalman filter theory. We propose an augmented state-space model for unknown system dynamics, largely composed of original state and system parameter vectors to embed time delay effect. A significant contribution of the proposed modeling technique is that the actual system state is modeled online simultaneously with parameter estimation. In practice, the system parameters are time-varying because of the non-stationary communication environment. We demonstrate from real-time experiments that our methodology allows online modeling of unknown dynamics with a wireless network topology.

This paper is organized as follows: In Section 2 our autonomous robot system is described and in Section 3 an augmented state-space model is proposed for the system. We derive a Kalman filter based estimation algorithm in Section 4 and analyze its convergence in Section 5. Real-time experiments and their results are provided in Section 6, and conclusions and future work are given in Section 7.

2. USN based autonomous robot systems

We construct an autonomous robot system whose state signal is transmitted to a host computer through the USN technique for online system modeling. Fig. 1 shows the autonomous robot implemented in this paper. Here, an embedded microcontroller ATmega128(L) module provides the core computing processor and a geared DC motor is connected to each of the four wheels, which are controlled from the microprocessor. The state of the system is measured online using embedded sensors. The USN module used in this paper is built with the CC2420 chip which is supported by the 802.15.4 standard communication and the 2.4GHz ZigBee protocols. A USN module is located in the remote robot and another in the host computer. The module in the robot sends its state signal acquired from the sensors to the USN module of the host computer. The received signal is used for modeling of robot dynamics by an estimation algorithm coded in the C++ programming language. A block diagram of the robot modeling system is shown in Fig. 2.

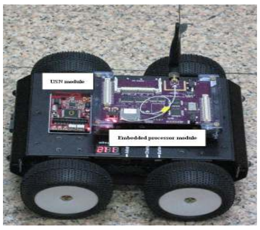

Fig. 1 Autonomous robot.

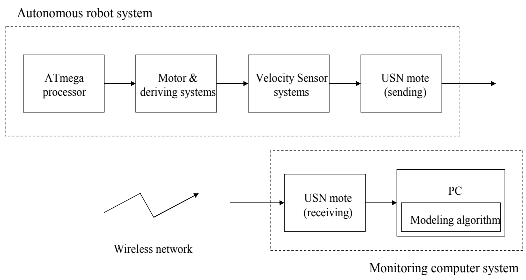

Fig. 2 System configuration of the USN-based robot modeling system.

3. System modeling of the robot system

We represent the robot system in Fig. 1 with a linear discrete model as

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k) + d(k) \tag{1}$$

where $x \in R^n$ is a state vector, u, y, $d \in R$ are input, output, and disturbance scalar respectively, and $A \in R^{n \times n}$, $B \in R^{n \times 1}$, and $C \in R^{1 \times n}$ are corresponding matrices. In (1) disturbance d is applied to observation as noise signal with Gaussian random statistics as

$$E[d(k)] = 0$$
$$E[d(k)d^T(k)] = Q$$
$$E[d(i)d^T(j)] = 0,\ i, j \in k, i \neq j \tag{2}$$

where $E[\cdot]$ is the expectation operator. The state measurement of the robot system is transmitted to the host computer through the wireless communication network but arrives after l cycles due to the network time delay (see Fig. 3). To include the time delay in the system dynamics, we rewrite the state space model as [11]

$$X(k+1) = \Phi X(k) + \Gamma u(k) + Wd(k)$$
$$z(k) = Hx(k) + m(k) \tag{3}$$

where the augmented state vector X includes the original state vector of (1) and l delayed observation vectors and is given by

$$X(k) = [x(k) y_1(k) y_2(k) \cdots y_l(k)] \in R^{n+l} \tag{4}$$

with

$$y_i(k) := y(k-i), \quad i = 1, 2, \cdots, l$$

Correspondingly, the related matrices are expressed as

$$\Phi = \begin{bmatrix} A & 0_{0\times(l-1)} & 0_{(n+l)} \\ C & 0_{1\times(l-1)} & 0 \\ 0_{(l-1)\times n} & I_{l-1} & 0_{(l-1)\times n} \end{bmatrix} \in R^{(n+l)\times(n\times l)} \tag{5a}$$

$$\Gamma = [B \quad 0_{l\times 1}]^T \in R^{(n+l)\times 1} \tag{5b}$$

$$W = [0_{n\times 1} \quad 1 \quad 0_{(l-1)\times 1}]^T \in R^{(n+l)\times 1} \tag{5c}$$

$$H = [0_{(n+l-1)\times 1} \quad 1] \in R^{1\times(n+l-1)} \tag{5d}$$

In (3), an observation noise m is similarly defined as a Gaussian random variable with the following properties:

$$E[m(k)] = 0$$
$$E[m(k)m^T(k)] = S$$
$$E[m(i)m^T(j)] = 0,\ i, j \in k, i \neq j \tag{6}$$

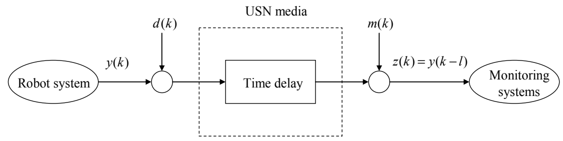

Fig. 3 Block diagram of network-based monitoring systems.

4. Kalman filter based parameter estimation

This Section presents an estimation methodology for the system in (1) using Kalman filter theory. First, we rewrite the state space model of (1) in the controllable form with state and input matrices respectively given by

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ & & & \vdots & & \\ 0 & 0 & 0 & \cdots & 0 & 1 \\ a_1 & a_2 & a_3 & & a_{(n-1)} & a_n \end{bmatrix} \tag{7a}$$

$$B = [0 \quad 0 \quad \cdots \quad 0 \quad 1]^T \tag{7b}$$

The parameter vector to be estimated in (7a) is given by

$$a = [a_1 \quad a_2 \quad \cdots \quad a_n]^T \tag{8}$$

For parameter estimation, we construct an augmented vector composed of the original state, the delayed observations, and the estimated parameter vectors of (8):

$$X_A(k) = [X(k) \quad a(k)]^T \in R^{2n+l} \tag{9}$$

The augmented state-space equation is given by

$$X_A(k+1) = f_A(X_A(k), u(k), d(k), k) \tag{10}$$

where $f_A(\cdot)$ denotes a nonlinear function. By applying (9) to (10), we have

$$\begin{bmatrix} X(k+1) \\ a(k+1) \end{bmatrix} = \begin{bmatrix} f_1(x(k), a(k), u(k), d(k), k) \\ f_2(a(k), d(k), k) \end{bmatrix} \tag{11}$$

where

$$f_1(\cdot) = \Phi(a,k)X(k) + \Gamma u(k) + Wd(k) \tag{12}$$

and $f_2(\cdot)$ is determined based on our model of the evolution of the parameter vector. Similarly, the output vector in (3) is rewritten as

$$z(k) = H_A X_A(k) + m(k) \tag{13}$$

where

$$H_A = [H \quad 0_{1\times n}] \in R^{1\times(2n+l)} \tag{14}$$

Next, we apply the well-known extended Kalman filter [12] to derive a parameter estimation algorithm for (11). Based on the Kalman filter, we obtain the state adjustment rule for (9) as

$$\hat{X}_A^+(k) = \hat{X}_A^-(k) + K(k)\big(\zeta(k) - H_A\hat{X}_A^-(k)\big) \qquad (15)$$

where ζ is the actual output measurement. This adjustment rule is formed with recursive computation and the estimated state vector in (15) is given by

$$\hat{X}_A^-(k) = \Phi_A(a,k-1)\hat{X}_A^+(k-1) + \Gamma_A u(k-1) \qquad (16)$$

where

$$\Phi_A = \begin{bmatrix} \frac{\partial f_1}{\partial X} & \frac{\partial f_1}{\partial a} \\ \frac{\partial f_2}{\partial X} & \frac{\partial f_2}{\partial a} \end{bmatrix}, \quad \Gamma_A = \begin{bmatrix} \Gamma \\ \frac{\partial f_2}{\partial u} \end{bmatrix} \qquad (17)$$

with partial differential terms

$$\left[\frac{\partial f_1}{\partial X}\right] = \Phi \in R^{(n+l)\times(n+l)} \qquad (18a)$$

$$\left[\frac{\partial f_1}{\partial a}\right] = \left\{\left[\frac{\partial \Phi}{\partial a}\right]X + \left[\frac{\partial \Gamma}{\partial a}\right]u\right\} \in R^{(n+l)\times n} \qquad (18b)$$

$$\left[\frac{\partial f_2}{\partial X}\right] = 0_{n\times(n+l)} \qquad (18c)$$

Since the function f_2 in (17) is dependent on the parameter model, we do not calculate the two partial differential equations $\partial f_2/\partial a$ and $\partial f_2/\partial u$ directly. In (15), the Kalman filter gain matrix is expanded as

$$K(k) = P^-(k)H_A^T\left[H_A P^-(k)H_A^T(k) + S\right]^{-1} \qquad (19)$$

where the covariance is updated using

$$P^-(k) = \Phi_A(a,k-1)P^+(k-1)\Phi_A^T(k-1) + W_A Q(k-1)W_A^T \qquad (20)$$

and $W_A = [W \;\; \partial f_2/\partial d]^T$. Finally, we obtain an adjustment rule for the covariance matrix

$$P^+(k) = \left\{\left[P^-(k)\right]^{-1} + H_A^T S^{-1} H_A\right\}^{-1} \qquad (21)$$

The block diagram of Fig. 4 summarizes the proposed parameter estimation algorithm.

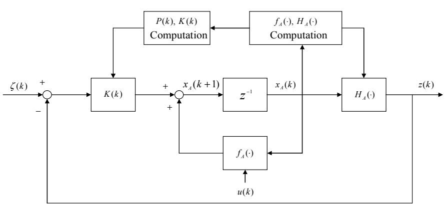

Fig. 4 Block diagram of the Kalman filter based modeling for the robot system.

5. Convergence property of the estimation algorithm

An estimated parameter vector in the proposed modeling algorithm must converge to a bounded limit with initial state condition and bounded input quantity. We study the convergence of the estimation algorithm using linear discrete system stability theory. We first expand the state estimation equation (15) by substituting (16) as

$$\hat{X}_A^+(k) = \left[\Phi_A(a,k-1) - K(k)H_A\Phi_A(a,k-1)\right] \hat{X}_A^+(k-1) + [I - K(k)H_A] \Gamma_A u(k-1) + K(k)\zeta(k) \qquad (22)$$

Applying z transformation to (22), we have

$$\hat{X}_A^+(k) = \left[\Phi_A - KH_A\Phi_A\right]z^{-1}\hat{x}_A^+(k) + \left[I - KH_A\right]z^{-1}\Gamma_A U(z) + K(k)\zeta(z) \qquad (23)$$

or

$$\{zI - \Phi_A + KH_A\Phi_A\}\hat{X}_A^+(k) = [I - KH_A]\Gamma_A U(z) + K(k)\zeta(z) \qquad (24)$$

For the Schur stability [13] of the discrete-time system, all the roots of its characteristic equation (25) must be inside the unit circle,

$$\left[I_n - KH_A\right]\Phi_A \qquad (25)$$

i.e. all the eigenvalues of the state matrix must be inside the unit circle. For more detail, letting its eigenvalues $\lambda_i = p_i + jq_i$, i=1,2,···, a sufficient condition for stability is that $|\lambda_i| = \sqrt{p_i^2 + q_i^2} < 1$.

6. Real-time experiment

We performed real-time experiments to evaluate our proposed estimation algorithm using the robot system of Fig. 1. We provide a sinusoidal input waveform with positive offset and select the robot steering velocity as the system output.

Fig. 5 shows the observed velocity measurement for the robot system. The velocity rise time for the robot is about 2 sec and is followed by persistent non-periodic oscillations of about 23 and 37 rpm. The observation in Fig. 5 is distorted by random sensor noise as expected in practice. We estimate state of the robot system based on the observation dataset of Fig. 5 by using the proposed modeling algorithm described in Section 4. We initialize the estimation algorithm with the covariance values of (2) and (6) as S=Q =100. The initial covariance and filter gain matrices $P(0)$ and $K(0)$ in (19) and (21) are assumed uniformly distributed in [-1, 1]. Fig. 6 shows a plot of the error between the actual observation and estimation signal defined by

$$e(k) = \sqrt{(\varsigma(k) - \hat{x}_1(k))^2} \qquad (26)$$

From Fig. 6, we observe a peak time of about 1 sec. The steady-state oscillations are drastically reduced with only a small non-periodic ripple with about 2 maximum rpm and 1 average rpm. The steady-state error of Fig. 6 is acceptable since noise is inevitable in wireless sensor networks and its effects cannot be completely eliminated. The time history of the estimated parameters is plotted in Fig. 7. Beginning from zero, the parameter

a_1 includes only positive numbers while a_2 is strictly negative during the time interval. However, the evolution pattern of the two waveforms is very similar to the error signal of Fig. 6 in that the trajectories include sustained oscillations. Although the robot system has non-stationary stochastic dynamics, the estimation algorithm adapts to obtain acceptable parameter estimates. Lastly, the trajectory of the filter gains is plotted in Fig. 8. The plot shows that the filter gains are adjusted to adapt to environmental changes resulting in similar oscillations to those observed in the plots.

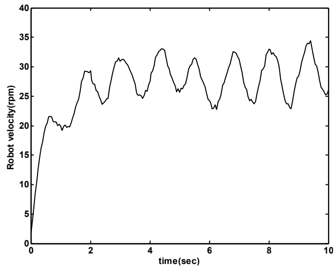

Fig. 5 Velocity state of the robot system.

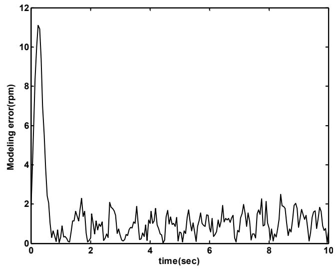

Fig. 6 Modeling error between the actual and estimated state sequences.

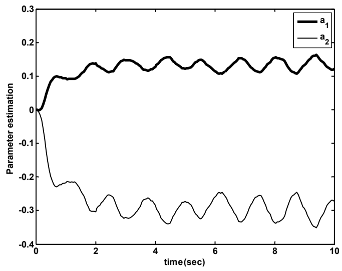

Fig. 7 System parameter estimates.

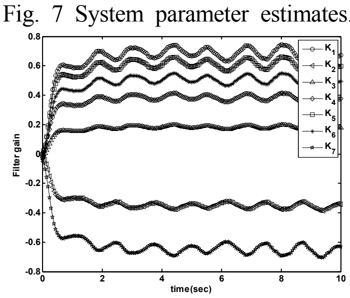

Fig. 8 Kalman filter gains.

7. Conclusions

This paper presents online modeling of an autonomous robot using an extended Kalman filter approach. The state of the robot system is transferred via the USN topology to the host computer where state estimation is achieved based on this observation. The modeling algorithm is formulated in terms of a discrete extended Kalman filter approach. The system model uses an augmented state composed of the robot state, time-delayed observations, and an estimated parameter vector. We conducted real-time experiments to evaluate our modeling method and our analysis of the estimation error sequence yielded satisfactory results. We summarize the contributions of this paper as follows: 1) Real-time experimental implementation for autonomous robot systems built with an embedded USN. 2) A new linear dynamic modeling algorithm using an augmented framework including the monitored system state and parameter estimation. 3) A state estimation algorithm using an enhanced Kalman filter method.

Future work will include control systems for autonomous robots using communication networks. We will investigate more advanced monitoring and distributed control mechanism for mobile multi-robot cooperative systems under the USN topology.

References

[1] D. Hristu-Varsakelis, W. S. Levine (Ed.), *Handbook of networked and embedded control systems*, Birkhäuser, Boston, 2005.
[2] K. Kang, J. Song, J. Kim, H. Park, and W.-D. Cho, "USS monitor: A monitoring system for collaborative ubiquitous computing environment," *IEEE Trans. on Consumer Electronics*, vol. 53, no. 3, pp. 911-916, 2007.
[3] M. Marciniak, "Reliability for future ubiquitous network societies challenges and opportunities," *Int. Conf. on Transparent Optical Networks*, vol. 3, pp. 130-131, 2006.
[4] G. Acampora and V. Loia, "Ubiquitous fuzzy computing in open ambient intelligence environments," *IEEE Int. Conf. on Fuzzy Systems*, pp. 923-930, 2006.
[5] J.-Y. Kwak, "Ubiquitous services system based on SIP," *IEEE Trans. on Consumer Electronics*, vol. 53, no. 3, pp. 938-944, 2007.
[6] T. C. Yang, "Networked control systems: a brief survey," *IEEE Proc.-Control Theory & Applications*, vol. 153, no. 4, pp. 403-412, 2006.
[7] Y. Jianyong, Y. Shimin, and W. Haiqing, "Survey on the performance analysis of networked control systems," *IEEE Int. Conf. on System, Manand Cybernetics*, pp. 5068-5073, 2004.
[8] Y. Tipsuwan and M.-Y. Chow, "Control methodologies in networked control systems," *Control Engineering Practice*, vol. 11, pp. 1099-1111, 2003.
[9] L. A. Montestruque and P. J. Antsaklis, "On the model-based control of networked systems," *Automatica*, vol. 39, pp. 1837-1843, 2003.
[10] L. Zhang, Y. Shi, T. Chen, and B. Huang, "A new method for stabilization of networked control systems with random delays," *IEEE Trans. on Automatic Control*, vol. 50, no. 8, pp. 1177-1181, 2005.
[11] Hyun C. Cho and Kwon S. Lee, "Nonlinear networked control systems with random nature using neural approach and dynamic Bayesian networks," vol. 6, no. 3, pp. 444-452, 2008.
[12] R. G. Brown, P. Y. C. Hwang, *Introduction to random signals and applied Kalman filtering*, Wiley, 1996.
[13] R. Greiner, "Necessary conditions for Schur-stability of interval polynomials," *IEEE Trans. on Automatic Control*, vol. 49, no. 5, pp. 740-744, 2004.