Extended Kalman Filter-Based Sensor Fusion for Operational Space Control of a Robot Arm

Rahim Jassemi-Zargani and Dan Necsulescu

***Abstract*—Accurate measurements of positions, velocities, and accelerations in both joint and operational space are required for achieving accurate operational space motion control of robots. Servomotors used for joint actuation are normally equipped with position sensors and optionally with velocity sensors for interlink motion measurements. Further improvements in measurement accuracy can be obtained by equipping the robot arm with accelerometers for absolute acceleration measurement. In this paper, an extended Kalman filter is used for multisensor fusion. The real-time control algorithm was previously based on the assumption of a jerk represented as a processed white noise with the zero mean. In reality, the accelerations are varying in time during the arm motion, and the zero mean assumption is not valid, particularly during fast accelerating periods. In this paper, a model predictive control approach is used for predetermining next-time-step jerk such that the remaining term can be modeled as Gaussian white noise. Experimental results illustrate the effectiveness of the proposed sensor fusion approach.**

***Index Terms*—Extended Kalman filter (EKF), multisensor fusion, operational space control, robot arm.**

I. Introduction

EXTENSIVE research has been carried out to achieve accurate operational space sensing and motion control of robot arms. Komada and Ohinishi [1] proposed a first-order lag filter as a perturbation observer for the estimation of the unknown dynamics terms used for linearization. Hsia *et al.* [2] and Youcef-Toumi and Fuhlbrigge [3] presented a similar method called the time-delay method, for obtaining the compensation terms. Hsia *et al.* [2] suggested a simple approach which basically uses the input and output torques of robot joints. For short time delay, the difference of these torques is added to the next torque input; this is feasible as long as the sampling time is very small. Robust controllers were designed to overcome the effect of some of the unknown dynamics terms. The adaptation of an impedance controller is proposed by Lu and Meng [4]. Also, an integral term for improving the robustness of the impedance controller was considered by Liu and Goldenberg [5]. Perturbation observers require the joint acceleration feedback signal, and joint accelerations can be measured or calculated. The calculation by numerical derivation of joint position assumes that high-resolution joint sensors are available. Because of high-frequency noise and other numerical problems, this signal requires a low-pass filter. Combining the end-effector accelerometers and joint position sensors can give an acceleration estimate with higher bandwidth than each separately. Sensor fusion between two sensors (accelerometers and resolvers) has been proposed in [6], [7]. A Kalman filter can be used for sensor fusion of these signals [7]–[9]. A complete three-dimensional virtual reality model for robotic systems is useful for motion visualization; however, for the operational space robot arm motion control an abstract world model, containing only joint and Cartesian motion variables, is sufficient [6], [10]. A proposed Kalman filter for obtaining an accelerometer signal was based on a kinematic model with a jerk assumed equivalent to a white noise [11]. This paper presents a model predictive control approach for replacing the pure white noise jerk assumption by a more realistic model containing a model-based predicted part and a Gaussian white noise part.

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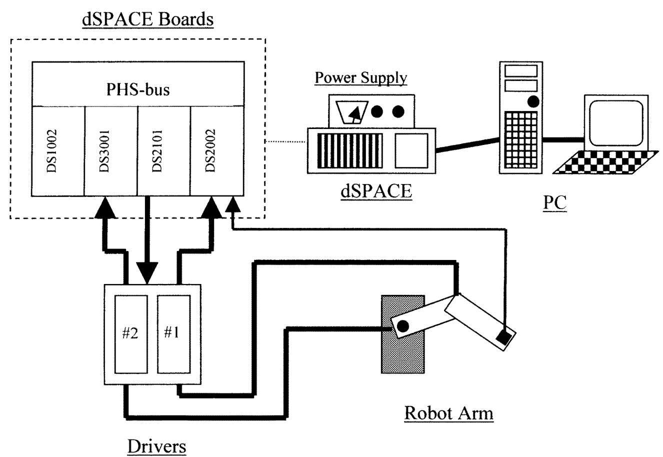

Fig. 1. Experimental setup for sensor fusion test.

II. Multisensor Measurement and Estimation of Accelerations

Accurate acceleration is needed for operational space motion control. There are different concurrent ways to obtain it, and sensor fusion is used for estimation based on the measurements obtained with various sensors. The approach presented in this paper is illustrated for the robot arm shown in Fig. 1. The experimental setup used for this purpose consists of a two-degrees-of-freedom planar robot arm, with each link being driven by a direct drive motor. All motors are connected to drivers controlled by the digital signal processing and control engineering (dSPACE) system, which executes the control program for the robot [12]. The dSPACE system consists of boards for data acquisition and a dSpace controller; a PC is used for interfacing.

Shoulder and wrist motors are equipped with 614 400 count/revolution and 409 600 count/revolution brushless resolvers, respectively [13]. The resolver accuracies are $\pm 30''$ and $\pm 60''$, respectively.

The results presented in this paper refer to a robot arm equipped with joint high-resolution resolvers for regular position measurement and with two orthogonal accelerometers located close to the free end of link two. The accelerometers are installed near the free end of the second link, one along the link, with $\pm$1-g acceleration range and 500-Hz frequency range, the other perpendicular to the link, with $\pm$2-g acceleration range and 200-Hz frequency range [14], [15]. A fourth-order Butterworth low-pass filter is used as the anti-aliasing filter with 120-Hz cut-off frequency [16].

High-resolution resolvers give accurate position measurements. Consequently, double numerical derivation of the position signal gives accurate but very noisy results

$$\ddot{\theta} = \frac{d^2}{dt^2}(\theta) \tag{1}$$

where $\theta =$ the vector of the joint angular position of joint 1 and 2.

Assume the vector x of the Cartesian position of the orthogonal accelerometers positioned close to the free end of link two. Joint acceleration can be calculated from the link accelerometer signals and estimated joint speed using the kinematic equation of the accelerations

$$\ddot{x} = J(\theta)\ddot{\theta} + \dot{J}(\theta)\dot{\theta} \tag{2}$$

such that

$$\ddot{\theta} = J^{-1}(\theta)\left[\ddot{x} - \dot{J}(\theta)\dot{\theta}\right] \tag{3}$$

where

- $\ddot{x}$ orthogonal accelerometer outputs;
- $\ddot{\theta}$ joint accelerations;
- $\dot{\theta}$ joint velocities;
- J Jacobian.

There are different ways of fusing these signals. Sensor fusion using an extended Kalman filter (EKF), for example, is more suitable for real-time estimation of joint accelerations given the presence of the noise and the nonlinearity of the robot arm dynamics. The EKF can estimate the states of nonlinear systems using a linearized approximation about the current state estimate [7].

Given θ_1 and θ_2 (robot joints 1 and 2 angular positions), the standard notation for state space equations is

$$\begin{aligned} x_1 &= \theta_1 \\ x_2 &= \theta_2. \end{aligned} \tag{4}$$

For a kinematic model, the resulting state equations are

$$\begin{aligned} \dot{x}_1 &= x_3 \\ \dot{x}_2 &= x_4 \\ \dot{x}_3 &= x_5 \\ \dot{x}_4 &= x_6 \\ \dot{x}_5 &= V_1 \\ \dot{x}_6 &= V_2 \end{aligned} \tag{5}$$

where joint angular jerks $\dot{x}_5$ and $\dot{x}_6$ are denoted as V_1 and V_2, respectively.

The following measurement equations define noisy measurements y_1 and y_2 of angular positions θ_1 and θ_2

$$\begin{aligned} y_1 &= x_1 + w_1 \\ y_2 &= x_2 + w_2 \end{aligned} \tag{6}$$

where w_1 and w_2 quantify the corresponding measurement noise.

Noisy measurements y_3 and y_4 of the Cartesian accelerations are used in measurement equations

$$\begin{bmatrix} y_3 \\ y_4 \end{bmatrix} = J(x_1, x_2)\begin{bmatrix} x_5 \\ x_6 \end{bmatrix} + \dot{J}(x_1, x_2, x_3, x_4)\begin{bmatrix} x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} w_3 \\ w_4 \end{bmatrix} \tag{7}$$

where

$$J(x_1, x_2) = \begin{bmatrix} j11 & j12 \\ j21 & j22 \end{bmatrix} \tag{8}$$

$$\dot{J}(x_1, x_2, x_3, x_4) = \begin{bmatrix} jd11 & jd12 \\ jd21 & jd22 \end{bmatrix} \tag{9}$$

and w_3 and w_4 quantify the corresponding measurement noise.

State equations in matrix form are [6], [7]

$$\begin{aligned} \dot{x} &= \overline{A}x + BV \\ y &= Cx + w \end{aligned} \tag{10}$$

where

$$\begin{aligned} x &= [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad x_6]^T \\ \dot{x} &= [\dot{x}_1 \quad \dot{x}_2 \quad \dot{x}_3 \quad \dot{x}_4 \quad \dot{x}_5 \quad \dot{x}_6]^T \\ y &= [y_1 \quad y_2 \quad y_3 \quad y_4]^T \\ V &= [0 \quad 0 \quad 0 \quad 0 \quad V_1 \quad V_2]^T \\ w &= [w_1 \quad w_2 \quad w_3 \quad w_4]^T. \end{aligned} \tag{11}$$

The state equations of the system for a short sampling time (T) are given by

$$\begin{aligned} x(n+1) &= ax(n) + bv(n) \\ y(n) &= cx(n) + w(n) \end{aligned} \tag{12}$$

where

$$\begin{aligned} a &\approx I + TA \\ b &\approx TB \\ v(n) &= V. \end{aligned} \tag{13}$$

The first two measurement equations, for y_1 and y_2, are already linear

$$\begin{aligned} y_1 &= x_1 + w_1 \\ y_2 &= x_2 + w_2. \end{aligned} \tag{14}$$

The third measurement equation, for y_3, can be linearized as follows [8]

$$y_3 = y_3(\hat{x}) + \left.\frac{\partial y_3}{\partial \overline{x}}\right|_{\overline{x} \approx \hat{x}} (\overline{x} - \hat{x}). \tag{15}$$

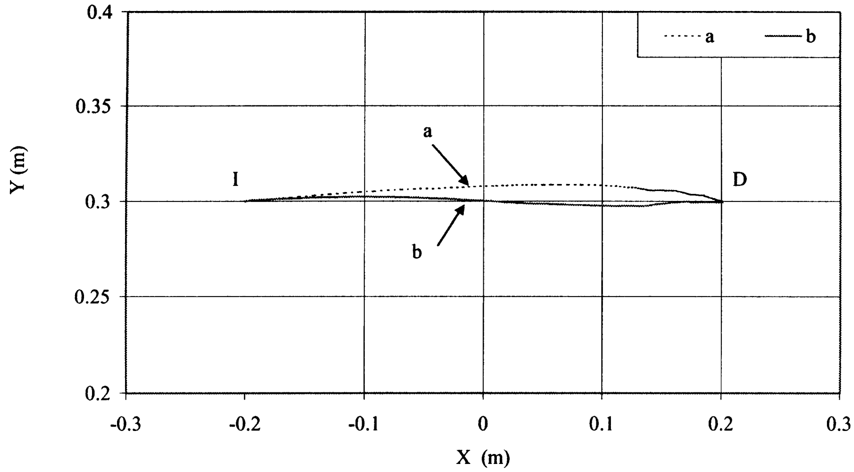

Fig. 2. Robot arm end-effector trajectory for acceleration estimation using (a) the second derivative of joint positions and (b) EKF sensor fusion.

The fourth measurement equation, for y_4, can be linearized as follows

$$y_4 = y_4(\hat{x}) + \left.\frac{\partial y_4}{\partial \overline{x}}\right|_{\overline{x}\approx\hat{x}} (\overline{x} - \hat{x}). \tag{16}$$

The EKF algorithm is well documented in the literature [8], [9]. Previous results were based on the assumption of a jerk represented as Gaussian white noise with zero mean [6], [7], [11]. Consequently, under this assumption, the jerks V_1 and V_2 in (5) are represented as time-independent white noise [7], [11]. In reality, the accelerations vary in time during the arm motion, and the zero mean assumption is not valid, particularly during fast acceleration periods. For the results presented in this paper, a model predictive control approach was used for predetermining next-time-step jerk such that the remaining term can be modeled as Gaussian white noise [17]. Experimental results illustrate the effectiveness of the proposed sensor fusion approach.

III. Experimental Results

Fig. 2 shows the resulting end-effector trajectories for the two-degrees-of-freedom planar robot from initial position (I) to the desired position (D). The results show that the trajectory obtained using accelerations from EKF-based sensor fusion was much closer to the ideal straight line trajectory than the trajectory based only on accelerations obtained from the second derivative of the position signals.

IV. Conclusion

The EKF approach to sensor fusion for acceleration estimation was improved by adding a new approach for predicting next-step-jerk values and thus overcoming the limitation of assuming a zero mean Gaussian white noise representation of jerks.

The experimental work proves that this sensor fusion approach can improve substantially the performance of a robot arm controller for trajectory generation; an almost straight-line trajectory was generated. The EKF method proved to be a reliable sensor fusion algorithm, which can fuse signals on-line for every sampling period. The algorithm improves observer bandwidth and produces a more accurate acceleration signal. The robot controller also remained robust when using the EKF.

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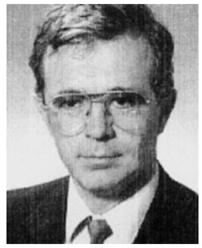

Dan Necsulescu worked as a Design and Research Engineer until he left Romania in 1980. In Canada, he started to work as a Nuclear Design Engineer with Ontario Hydro. In the Fall of 1980, he joined the Department of Mechanical Engineering, University of Ottawa, Ottawa, ON, Canada, where he carried out teaching, research, and administrative duties, including Chair of Mechanical Engineering, from 1990 to 1993, and is currently Director of the Engineering Management Program. He carried out collaborative research with various companies and governmental organizations including CRC, Thomson CSF Systems Canada, and the Canadian Space Agency. His research interests are dynamics and control of mobile robots, impedance control of dual arm robots, dry friction compensation in servomotors, and real-time failure detection in intelligent structures.