Sensor Fusion for Long-Reach Manipulators: System Description and Initial Experiments

Klaus Obergfell, Wayne J. Book and James D. Huggins
George W. Woodruff School of Mechanical Engineering
Georgia Institute of Technology
Atlanta, Georgia 30332

1. Introduction

Precise knowledge of the end-effector position of long-reach, lightweight manipulators is important because the inherit flexibility can cause deflections and vibrations of the structure. A non-contact, low-cost position measurement is desirable for practical purposes. Our previous work focused on computer vision based methods to achieve this goal, see also [Obergfell and Book, 1992]. These investigations indicated sampling time and range or resolution limitations for the chosen approach. But alternative methods using a single sensor currently have similar limitations, e.g. drift, non-direct measurement, price. To solve these problems we consider sensor fusion, combining measurements from separate sources to yield faster and better position measurements. This approach is especially interesting for robotics applications since most robots are already equipped with the necessary sensors. We are planning to implement these methods on our manipulator testbeds: First on a one-link flexible manipulator and later on a two-link flexible long-reach manipulator. The robots are currently equipped with joint angle sensors, tachometer, strain gages and tip accelerometer.

2. Long-Reach Manipulators

2.1. Characteristics of Long-Reach Manipulators

The links of a manipulator for a large workspace are slender beams for all practical purposes. Since the cross-section of such links is relatively small in comparison to the length it is important to consider the link deformation for modeling and control. Deflection, torsion and elongation deform a manipulator during motion. But the major deformation for a typical manipulator considered in this work results from transverse deflection of the links. Other deformations are not considered further. The dynamics of link deflection can be described by the Euler-Bernoulli beam equation. A practically sufficient approximation of the link deflection is the finite sum in equation (1),

$$w = \sum \phi_i(q)$$

where \(w\) is the link deflection, the spatial variables \(\phi_i\) are the assumed mode shapes and the temporal variables \(q\) are the generalized modal coordinates. Many methods are available to choose the mode shapes.
A solution of the Euler-Bernoulli equation
\[ w(x,t) = \sum_{k=1}^{n} X_k(x) \cdot q_k(t) \]  

(1)

\[ X_k = A_k \cosh(\beta_k x) + B_k \cos(\beta_k x) + C_k \sinh(\beta_k x) + D_k \sin(\beta_k x) \]  

(2)
is one possibility. The constants \( A_k - D_k \) depend on geometry and material properties of the beam, the chosen boundary condition and the corresponding natural frequency as indicated by the index \( k \).

Now we are able to formulate the equations of motion for a flexible manipulator. For a one-link manipulator those are given by Kwon (1991):

\[ M \ddot{q} + D \dot{q} + K q = B \tau \]  

(3)

\[ q^T = [ q_0 \quad q_1 \ldots \quad q_n ] \]

The vector \( q \) has \( n+1 \) elements. These elements are the generalized rigid body coordinate \( q_0 \) and the generalized modal coordinates \( q_1, \ldots, q_n \). These are the quantities to be determined.

### 2.2. Experimental Long-Reach Manipulator Testbeds

Two testbeds are currently available for experimental manipulator studies at the Georgia Tech Manufacturing Research Center. They are denoted RALF (Robot Arm Large and Flexible) and SLIM (Single Link Manipulator).

RALF is a 2-link manipulator restricted to motion in the vertical plane. The structure consists of two 3.048m (10 foot) long links and a parallel link mechanism. The manipulator is actuated with two hydraulic cylinders and controlled from a 486-PC. It is equipped with joint position sensors, strain gages and tip accelerometer. A Landmark Tracking System (LTS) as described in [Obergfell and Book, 1992] was previously used for end-point measurements and control.

SLIM is a single-link manipulator operating in the horizontal plane. Its four foot long flexible link is actuated with an electric motor and controlled through a 486-PC. SLIM is equipped with a joint angle sensor, tachometer and several strain gages mounted along the link. Tip position measurements were previously not available. In the following we will use SLIM as an example for implementations. These techniques can be extended later to more complex structures like RALF.
3: Sensor Fusion Problem

3.1. Overview

For our purposes we use the term sensor fusion to describe the process of combining measurements from separate sensors to yield better or more complete results than an individual sensor could provide. In this publication we are addressing the issue of combining measurements from separate sources as well as choosing and placing sensors. Various approaches for combining measurements to yield the best estimate of physical quantities are described in the literature. Harmon et al (1986) distinguished between averaging method, deciding method and guiding method.

An averaging method computes a weighted sum of the data to estimate the observed quantities. The weights are proportional to some measure of confidence, which can be based on statistical data or other knowledge about the sensors. Two well known examples of the averaging method are Kalman filter and maximum-likelihood estimation. A deciding method chooses the measurement with the highest level of confidence as the estimate of the measured quantity.

A guiding method differs from the two other methods through the dependence between sensors. In the averaging and deciding methods the sensors operate independently, while the guiding method utilizes a master/slave scheme to control sensors. This is best explained with an example: Two position sensors, one with a large range but low resolution (master) and another with a small range but high resolution (slave), could be used for accurate position measurements over a large workspace. For this the lower resolution sensor observes the whole workspace and guides the higher resolution sensor to the area of interest.

The averaging method and especially the Kalman filter is the method used most often for sensor fusion in robotics: Dickmanns and Christians (1989) exploited the recursive filtering idea of Kalman for image sequence analysis for autonomous road vehicles. Hashimoto et al (1992) integrated the navigation of a mobile robot using the extended Kalman filter. Nam and Dickerson (1991) fused measurements from accelerometer and vision to yield position estimates. Zhang and Zhang (1992) investigated the maximum-likelihood estimator for joint torque sensing. Promising is also the combination of the above methods. For example a combination of the deciding and the averaging methods could be used to reject bad measurements before the average is taken, preventing corruption of the estimate. Another possibility is the combination of guiding and averaging method to adjust the weights used for averaging. Murphy (1991) describes a general sensor fusion architecture for robotics that selects the fusion method depending on the task.

3.2. Kalman-Filter and related Techniques

The Kalman filter is a recursive state estimator for a linear system with additive noise disturbance which is observed by noisy measurements. The plant and measurement equation for such system are where $x$ is the unknown state vector, $z$ is the measurement vector and $w$ and $v$ are uncorrelated white noise
sources. The state estimate of the filter is optimal if the statistics (mean and covariance matrix) of plant noise w and measurement noise v and an initial state estimate are known. The extended Kalman filter applies to non-linear systems. The details of the filtering algorithm are omitted for space constraints. The reader is referred to the literature, [Lewis, 1986] and [Brown, 1983]. But it is interesting to note some special cases and connections to other estimation methods.

The maximum-likelihood estimator applies to a situation where only prior knowledge about the measurement process and nothing about the state is available. A recursive formulation of the maximum-likelihood estimator can also be derived. It can further be shown that the recursive maximum-likelihood estimator is equivalent to the Kalman filter for a constant system without prior knowledge about the state. This makes the design of an estimator for a static system easy - if we have no prior knowledge of the state we pick the maximum-likelihood estimator. Otherwise we pick the Kalman filter which gives better results but requires more computations. The decision for a dynamic system is not as easy. The Kalman filter produces better error covariances after several iterations than the maximum-likelihood estimator, even when no initial state estimate is available. But the error covariance might not be very meaningful when the knowledge about the plant noise is vague or we have assumed that the plant is deterministic. In this case the maximum-likelihood estimator can be used to analyze the worst case performance of a Kalman filter. (Note that the measurement noise model is readily obtainable from prior experiments with the sensors).

4. Sensor Fusion Algorithm for One-Link Flexible Manipulator (SLMF)

We propose to use the existing joint angle sensor and strain gages and an additional end-point position sensor to estimate end-point position and generalized modal coordinates of SLMF as displayed in Figure 1. This setup provides very accurate direct measurements of hub angle and end-point position while the strain measurements provide additional information to separate the generalized modal coordinates in equation (1). In order to formulate the Kalman filter equations we need to derive plant and measurement models and the associated noise statistics. The plant dynamics is given in equation (3) but no noise model has been established at this point. The measurement model is explained in the following, assuming 2 generalized modal coordinates and pinned-pinned boundary conditions.
4.1. Relations between Manipulator Coordinates and Measurements

The notations used are explained in Figure 2. Two moving coordinate systems are displayed in this figure corresponding to different boundary conditions (B.C.). The coordinate system \((i_1, j_1)\) describes the clamped-free B.C. which may appear more natural, but the pinned-pinned B.C. \((i_2, j_2)\) is used here since it offers computational advantages with the control method used. Since the length of the manipulator link is large relative to the deflection of the link, we assume that the measured deflection equals the actual deflection.

The "deflection" at the end of the link is zero due to this particular choice of coordinate system. The end-point deflection measurement is related to the flexible mode coordinates through the slope of the hub deflection

\[
w'(x=0) = \frac{d}{dx} X_1(x) \big|_{x=0} q_1(t) + \frac{d}{dx} X_2(x) \big|_{x=0} q_2(t) = \Theta(t) - q_0(t) = \frac{w^*(t)}{L} \quad (5)
\]

where \(w'\) denotes the end-point deflection measurement. Therefore the measurement is a linear combination of the general mode coordinates.

\[
w^*(t) = c_1 q_1(t) + c_2 q_2(t) \quad (6)
\]

The constants \(c_1\) and \(c_2\) are non-zero and have the same sign as can be seen from the mode shapes.

The hub-angle measurement is related to rigid body coordinate and end-point deflection measurement by

\[
\Theta^*(t) = q_0(t) + \frac{w^*(t)}{L} = q_0(t) + c_1 q_1(t) + c_2 q_2(t) \quad (7)
\]

where \(\Theta^*\) denotes the measurement. Therefore the hub-angle measurement is a linear combination of all
three generalized coordinates.

A strain measurement at position \( l \) on the link is related to the second spatial derivative of the deflection function as given in equation (8), where \( \varepsilon^* \) denotes the strain measurement.

\[
\frac{M}{EI} = \frac{\varepsilon^*(t)}{h} = w''(x=l,t) = \frac{d^2}{dx^2} X_1(x)|_{x=l} q_1(t) + \frac{d^2}{dx^2} X_2(x)|_{x=l} q_2(t)
\]

\[
\varepsilon^*(t) = c_3 q_1(t) + c_4 q_2(t)
\]

Therefore the measurement is again a linear combination of the generalized modal coordinates.

4.2. Sensor Accuracy

The sensor models for the existing joint angle sensor and strain gages are omitted here, the reader is referred to [Hastings, 1986] and [Huggins, 1988]. The added end-point position sensor is a position sensing photodiode which measures the translation of an infrared LED mounted to the tip of the manipulator. The actual photodiode is mounted in a lens adapter for 35 millimeter camera lenses. For a given distance a lens can be chosen that gives the desired position measurement range. The active sensor area is a narrow strip of 30 by 4 millimeter which makes the sensor very sensitive to rotations. This makes it necessary to calibrate the sensor on the manipulator.

The sensor was initially calibrated using a x-y table. For this calibration we chose a setup that would
work for both manipulators described in this paper. We chose a distance of 3.048m (10 feet) between sensor and light source which equals the length of a link of RALF. This setup can easily be modified to work on SLIM, since the illumination power is rather a problem over long distances. Several tests were necessary to find a light source that illuminated the sensor sufficiently over the chosen distance. A laser-diode worked, but only for very small translations which were smaller than the deflections of the large manipulator. After testing several infrared LED’s we decided to use a narrow beam, high power infrared LED. The lens used was a F 5.6 tele-zoom lens, set to a focal length of 300 millimeter. This lens provides a maximum position measurement range of 30.48cm (12 inch) for the 3.048m (10 feet) distance.

Plots indicating the linearity and noise are displayed in Figure 3. Both plots contain two data sets, one was taken with regular room illumination turned on and the other with the room illumination dimmed down (denoted off in the plots). The linearity of the voltage versus position curve is very good with a regression coefficient of 0.999 for a first order fit. A third order fit improves the regression coefficient to 0.9999. The lighting conditions don’t seem to effect the linearity of the measurement. The peak-to-peak noise is acceptable. For the described conditions the measured noise would be equivalent to a position error of less than 0.4 millimeter. A rigorous statistical analysis of the measurement noise has yet to be performed but a check of the noise spectrum showed that the frequency response of the measurement noise is spread out and does not contain any significant peaks, i.e. it can be described by white noise. The lighting has a noticeable effect on the measurement noise which increased by up to 20 percent when the room illumination was turned on.

**Figure 3:** Noise of position measurement using position sensing photodiode

**Figure 3a:** Linearity of position measurement using photodiode.
5. Future Work

Currently we are in the process of manufacturing the sensor mounts necessary to calibrate the system on the manipulator. Once this is completed and the sensors are working properly the statistical analysis of the measurement noise has to be completed. A minor issue in this context is to test if a visible light blocking filter can decrease the noise as indicated by our initial calibration. Parallel to these projects we are working on a theoretical analysis of the plant noise. After all this is accomplished we will be ready to implement the Kalman filter.

References

