Industrial Robot Tool Position Estimation using Inertial Measurements in a Complementary Filter and an EKF

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Abstract: In this work an Inertial Measurement Unit is used to improve tool position estimates for an ABB IRB 4600 industrial robot, starting from estimates based on motor angle forward kinematics. A Complementary Filter and an Extended Kalman Filter are investigated. The Complementary Filter is found to perform on par with the Extended Kalman Filter while having lower complexity both in the tuning process and the filtering computations.

Keywords: Inertial measurement units, Position estimation, Industrial robots, Complementary filters, Extended Kalman filters

1. INTRODUCTION

Industrial robot tool position control relies heavily on model-based feedforward, with a feedback loop based on motor angle measurements. When models are not accurate enough additional measurements can be used to improve the accuracy of the tool position estimate. One possibility is using inertial measurements, i.e. acceleration and angular velocity, of the tool. This work experimentally investigates how an Intertial Measurement Unit (IMU) mounted on the robot tool can improve on estimates obtained from forward kinematics based on motor angles.

Position estimation based on inertial measurements is a well studied problem, and in this light, the contributions of this work are:

• The application to a 6-DOF industrial robot using highly accurate reference sensors, giving a qualitative feel for possible performance.

• Investigating the Complementary filter (CF) for this kind of application, finding that it performs similarly to the more well-known Extended Kalman filter (EKF) and analysing the reasons behind this.

2. RELATED WORK

For a general introduction to IMU-based estimation see for example Hol (2011). In the area of industrial robots, similar work has been carried out in Olofsson et al. (2016) and Chen and Tomizuka (2014). The former is similar to the present paper in scope; an EKF was compared to a Particle filter (PF) instead of a Complementary filter. In the latter, a flexible-joint model of the robot is used, and joint-angles are estimated using individual KF’s.

The idea behind the Complementary filter was first introduced in a patent, Wirkler (1951), and the name was, to the authors’ best knowledge, introduced in Anderson and Fritze (1953). The method has been well studied in the context of IMU-based estimation, especially attitude estimation. An introduction to the CF in that context is given in Jensen et al. (2013). For an illuminating discussion of the relation between complementary filtering and Kalman filtering see Brown (1972), also in the context of inertial navigation. Regarding robotics there are examples of CF applications in Roan et al. (2012), where it was applied to joint angle estimation on a humanoid robot, and Wallén et al. (2014), where it was applied to a parallel kinematic robot.

3. SYSTEM OVERVIEW

The experimental setup used in this work consists of an industrial robot with motor angle measurements, an IMU mounted on the robot tool and a high-precision tracking system for reference measurements. A more detailed presentation of the setup is given in Norén (2014).

3.1 Industrial Robot

The industrial robot used in the experiments is an IRB4600, shown in Figure 1. The robot is rated for a 45 kg
payload, weighs around 420 kg and is roughly 2.4 meters in upright position, see ABB (2016) for details.

For purposes of estimation the robot is modelled using kinematics only, i.e. dynamic effects like friction or flexibilities are not modelled.

### 3.2 Inertial Measurement Unit

The sensor for measuring acceleration and angular velocity is a STIM300 IMU, which can be considered a high-end IMU, see Sensoron AS (2016) for specifications. In Figure 1 the sensor is shown mounted on the robot. To be able to use the sensor measurements and relate the measured acceleration and angular velocity to the robot motion it is necessary to estimate the position and orientation of the sensor relative to the robot. The first step in the algorithm, Axelsson and Norrlöf (2012), is to compute the internal parameters of the sensor, scaling and offset, and the orientation of the sensor with respect to the robot. In the second step the position of the sensor is estimated by moving the robot. For details see Norén (2014).

### 3.3 Sensor for Evaluation Purposes

An LTD840 laser tracker system from Leica Geosystems was used to obtain accurate position measurements for use as a reference. The system has an accuracy on the order of 0.1 mm in the conditions under consideration, Leica Geosystems (2016), and measurements are provided at 1 kHz sample rate. A limitation of this system is that it does not provide orientation measurements.

### 4. ESTIMATION METHODS

#### 4.1 Complementary Filter

Complementary filtering is a way of approaching the problem of fusing measurements/estimates with different noise characteristics.

The idea of the complementary filter is that in the absence of measurement noise the filter should be a perfect estimator. That is, there should be no dynamics between the true signal and the estimate, as those dynamics would distort the estimate even with perfect measurements. This is referred to as the complementary constraint. Other terms found in literature are distortionless filtering and exact dynamic filtering, Brown and Hwang (1997). It can also be viewed as a min-max approach, Brown (1972).

In the case where nothing is known about the statistical properties of the true signal, i.e. the process noise completely dominates the measurement noise, any optimal estimate will satisfy the complementary constraint.

As such, a complementary filter is equivalent, as is any linear filter, to a Kalman filter derived under certain assumptions on the system. The principle behind the complementary filter is essentially the same as behind the so called error-state or indirect Kalman filter, Brown (1972) and Maybeck (1979).

Having, by the choice of complementary filtering, assumed that the underlying signal is unpredictable the only remaining design parameters are the assumptions on the relative spectral power densities of the measurement noise signals.

Let \( \hat{p}_{fk} \) be the forward kinematics position estimate and \( \hat{p}_{imu} \) the position estimate obtained from integrating the IMU signals:

\[
\hat{p}_{fk} = p + v \\
\hat{p}_{imu} = p + w
\]  

Here \( p \) is the true position and \( v \) and \( w \) are noise terms representing the errors in the estimates. Then in order to satisfy the complementary constraint the final estimate has to be of the following form, given in transfer function notation:

\[
\hat{P}(s) = G(s)\hat{P}_{fk}(s) + (1 - G(s))\hat{P}_{imu}(s) \\
= P(s) + G(s)V(s) + (1 - G(s))W(s)
\]  

Thus we see in equation (2) that the filter \( G(s) \) only affects the error terms, and we want to choose \( G \) as to minimize the contribution of the error terms \( V(s) \) and \( W(s) \) to \( \hat{P}(s) \).

When the noise terms have a low- and high-frequency character respectively, the tuning process reduces to choosing a cut-off frequency for the filter \( G(s) \) and an appropriate roll-off. Here, the low-frequency information is in the forward kinematics as that estimate has no temporal drift, but fails to account for dynamic effects such as link flexibility and friction. The IMU-measurements on the other hand have a low-frequent bias drift, but captures rapid changes well.

Implementation and tuning of the complementary filter was done manually in a matter of hours, and resulted in choosing \( G(s) \) as a second-order low-pass filter with a cut-off frequency of slightly less than 30 Hz.

The estimated states were tool position in world coordinate frame and tool orientation as a quaternion. The filtering was performed in two steps, first the orientation estimate was updated and this update was then used to align the acceleration measurements with the world coordinate frame before integrating and updating the position estimate.

For simplicity, the same filter was used for all estimated states. A natural extension would be to tune different filters for the position and orientation estimates.

#### 4.2 Extended Kalman Filter

The Kalman filter (KF) and its extension to non-linear systems in the form of the Extended Kalman filter (EKF) are well-known methods, see for example Gustafsson (2012) for more details.

The Kalman filter is an optimal solution to the linear filtering problem with Gaussian noise, in the sense that its estimates are unbiased with minimum variance. The Kalman filter approach relies on models of the system dynamics and has a large number of design parameters compared to the complementary filter.

In the Extended Kalman filter basically the same algorithm is used as in the KF, but the nonlinear equations...
are linearized around the current state estimate at each timestep. In the non-linear case the optimality of the KF is lost, but given "nice" non-linearities it is reasonable to expect the EKF to perform well.

Here, robot tool position is modelled by a constant acceleration model and tool orientation by a constant angular velocity model. The IMU is further modelled as having a separate bias for each axis and type of signal, giving the states of the EKF as position, velocity and acceleration of the tool in the world reference frame, orientation as a quaternion, angular velocity in the sensor frame and finally sensor biases:

\[ x = [p, v, a, q, \omega, b_{acc}, b_{gyr}] \]  

(3)

Time update equations are straightforward given the constant-acceleration and constant-velocity assumptions, see for example Gustafsson (2012). The measurement equations can be written, with scaling factors from calibration omitted for simplicity, as:

\[
\begin{align*}
    y_p &= p + e \\
    y_q &= q + e \\
    y_{acc} &= R_{IB}^T(a + g) + b_{acc} + e \\
    y_{gyr} &= \omega + b_{gyr} + e
\end{align*}
\]  

(4)

Where \( y_p \) and \( y_q \) are the forward kinematic estimates, \( y_{acc} \) and \( y_{gyr} \) the IMU-measurements, \( e \) represents measurement noise, \( R_{IB}^T \) a rotation from the world frame to the IMU-frame and \( g \) gravity.

The EKF was tuned using a genetic algorithm for global optimization, which was left to run for a total period of several days. This resulted in a model with estimated process noise ten orders of magnitude larger than the estimated measurement noise.

5. TRAJECTORIES

Two trajectories were used for experimental evaluation.

The first, shown in Figure 2, followed a benchmark path for industrial robots, part of the ISO 9283:1998 standard. It has previously been presented in Moberg and Hanssen (2009). For this trajectory the target tool speed was 200 mm/s.

The second is a cube with side 30 mm, shown in Figure 4, where the target speed was 80 mm/s with brief stops in the corners.

In both trajectories the tool orientation was kept constant, as the laser tracking system requires line of sight and furthermore cannot measure orientation.

6. EXPERIMENTAL RESULTS

The performance of the estimation methods for the two test trajectories is summarized in Table 1, were it can be seen that the CF and the EKF provide similar results in terms of root mean square error, with the CF performing slightly better on the slower of the two trajectories.

The estimates are visualized in Figure 2 and Figure 4. A close-up of some interesting features from the ISO trajectory is shown in Figure 3.

Characteristic parts of the time-error plots for the two trajectories are shown in Figure 5 and Figure 6 respectively.
Fig. 4. Estimates from the cube trajectory, using a target tool speed of 80 mm/s and high precision mode, i.e. stopping briefly at each corner.

Table 1. Root mean square error for the test trajectories and estimation methods.

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>CF</th>
<th>EKF</th>
<th>FK</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISO</td>
<td>0.95 mm</td>
<td>0.94 mm</td>
<td>1.44 mm</td>
</tr>
<tr>
<td>Cube</td>
<td>0.81 mm</td>
<td>0.93 mm</td>
<td>0.79 mm</td>
</tr>
</tbody>
</table>

Fig. 5. Estimation error during part of the ISO-trajectory. The two wide peaks after 5 s corresponds to the circle and the rapid succession of peaks corresponds to the series of 90° turns.

7. DISCUSSION

The difference in performance for the forward kinematics estimate, as shown in Table 1, between the two trajectories is notable. This is probably due to lower accelerations in the cube trajectory, as the forward kinematics does not capture the dynamic properties excited by acceleration, such as flexibilities in links and gearboxes. This can be supported by comparing the time-error plots and the trajectories, where a clear connection is seen between acceleration and forward kinematics error. E.g. the circle and the rapid succession of 90°-turns in the ISO trajectory can clearly be seen as error peaks for the forward kinematics in Figure 5.

The CF and the EKF estimates, using measurements of the acceleration, are not sensitive in the same way. It is, however, clear that several sections can be found where the forward kinematics outperforms both filtering approaches, also in the ISO trajectory, showing how IMU measurement noise is limiting the accuracy of the position estimates.

That the two filtering approaches perform similarly is not surprising given the large ratio between process and measurement noise that the EKF tuning resulted in, as such a ratio is essentially another way of stating the assumptions behind complementary filtering.

In retrospect it is also not surprising that these trajectories, containing parts with quite different characteristics, are not well described by a constant-acceleration model with stationary Gaussian process noise.

As the tool orientation could not be measured, it was kept constant during both trajectories, and nothing conclusive can be said regarding the accuracy of the orientation estimates. However, since the orientation estimate is crucial for converting acceleration measurements from the sensor coordinate frame to the world coordinate frame, poor orientation estimates would most likely have had a large negative impact on the position estimates.

8. CONCLUSIONS

By combining the motor angular measurements of an industrial robot with measurements from an IMU mounted on the robot tool, better estimates of the tool position can be achieved compared to using only direct kinematics from motor angle measurements. The forward kinematics estimates deteriorate in parts of the trajectory containing large accelerations, and this is where the filtering approaches offer an improvement.

Between the Complementary filter and the Extended Kalman filter there was no major difference in performance, the CF performed slightly better during the slower trajectory. This, as well as the large process noise ob-
tained when tuning the EKF, suggests that the statistical properties of the tracked signal are not well described by the chosen motion models and the Gaussian distributions available in the Kalman framework.

When this is the case, using a Complementary filter might yield results comparable those of an EKF, while having both a less complex tuning process and lower computational complexity.

REFERENCES


