KALMAN FILTER BASED LOCALIZATION AND TRACKING ESTIMATION FOR FINE-SCALE RFID SYSTEMS

QIAN YANG, DAVID G. TAYLOR, GREGORY D. DURGIN

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Outline

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✓ Variable-gain Kalman filter 2

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- Conclusion

MOTIVATION: FINE-SCALE RFID MOTION CAPTURE & LOCALIZATION SYSTEMS

REVIEW

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MOTIVATION: FINE-SCALE RFID MOTION CAPTURE & LOCALIZATION SYSTEMS

- Remote motion capture, and tracking in robotic wayfaring, virtual reality.
- Body movement detection by combining passive UHF RFID with Support Vector Machine classification technique together [Amendola 2015].
- Among all RFID localization and tracking systems, hybrid schemes have the highest accuracy (5-400 cm) and largest range (hundreds of meters) by combining a variety of sources.

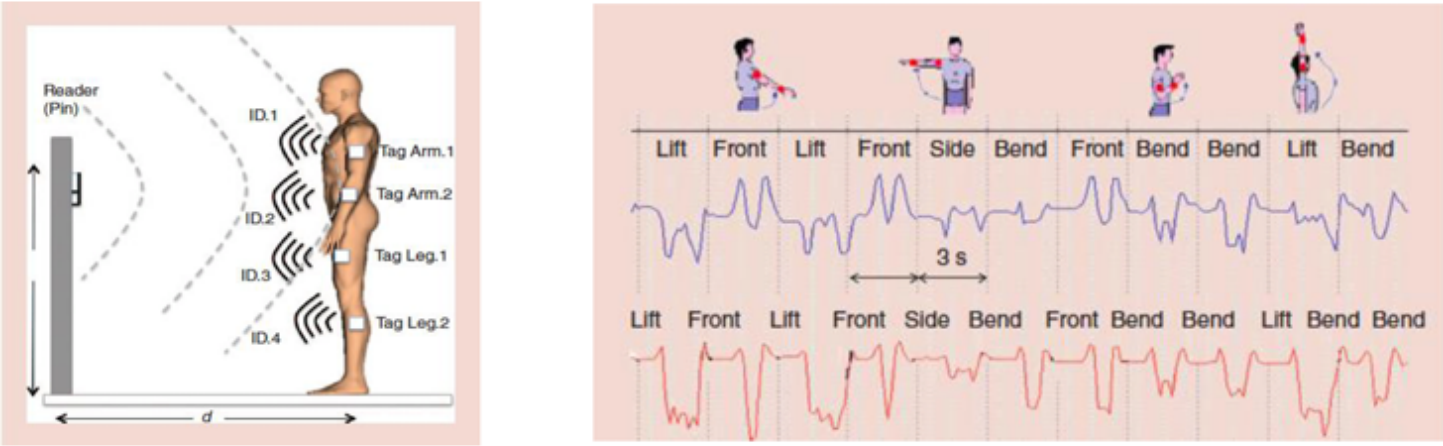

Fig. 1 Movement Detection by Synergizing Passive RFID and Machine Learning [Amendola 2015]

HIMR RFID SYSTEM DESCRIPTION

MM-SCALE LOCALIZATION AND TRACKING

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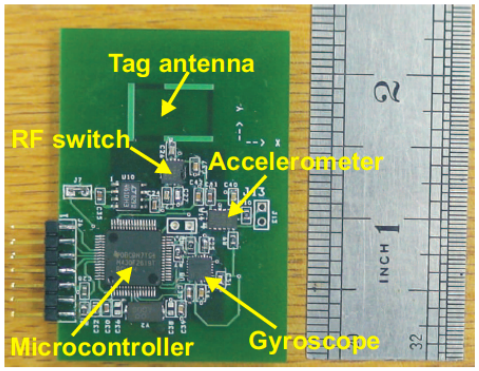
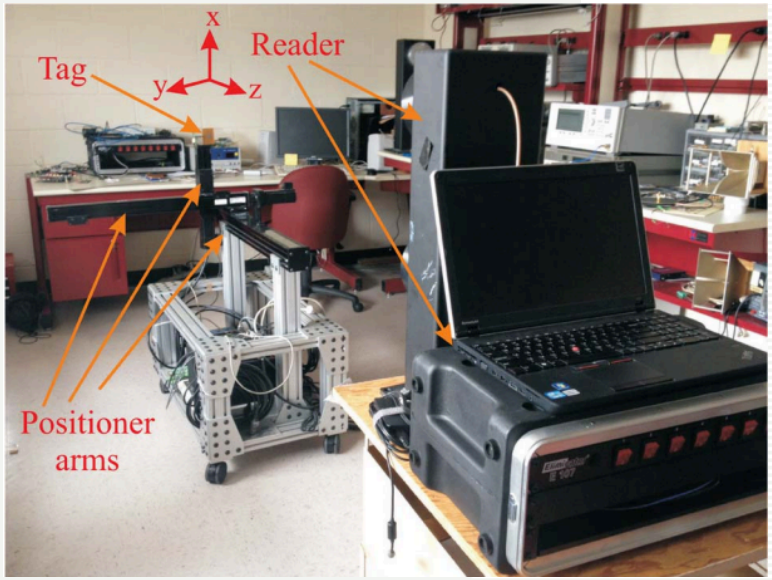
HYBRID INERTIAL MICROWAVE REFLECTOMETRY (HIMR) RFID SYSTEM SET-UP





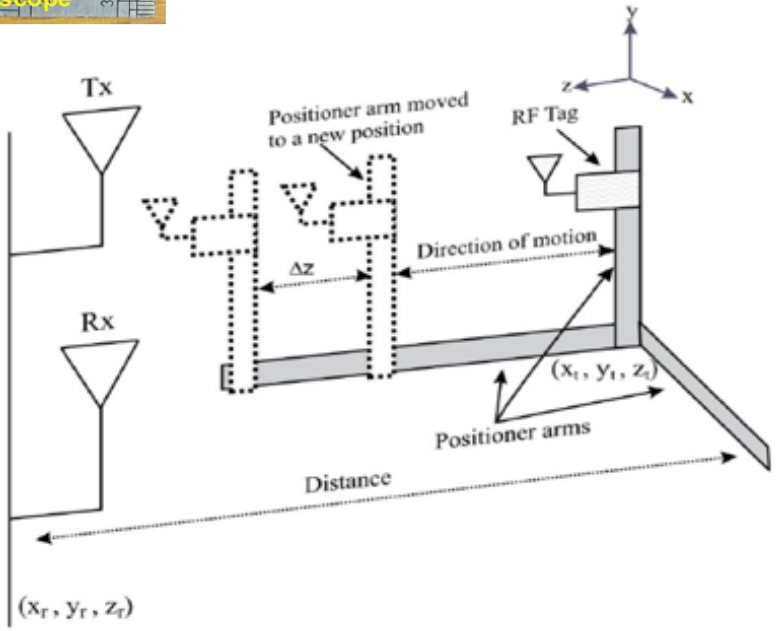


Fig. 2 Set up of HIMR RFID Localization and Tracking (L&T) System [Akbar 2015]

KALMAN FILTER BASED ESTIMATION

FOR HIMR RFID SYSTEM

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PROPOSED KALMAN FILTER ESTIMATORS

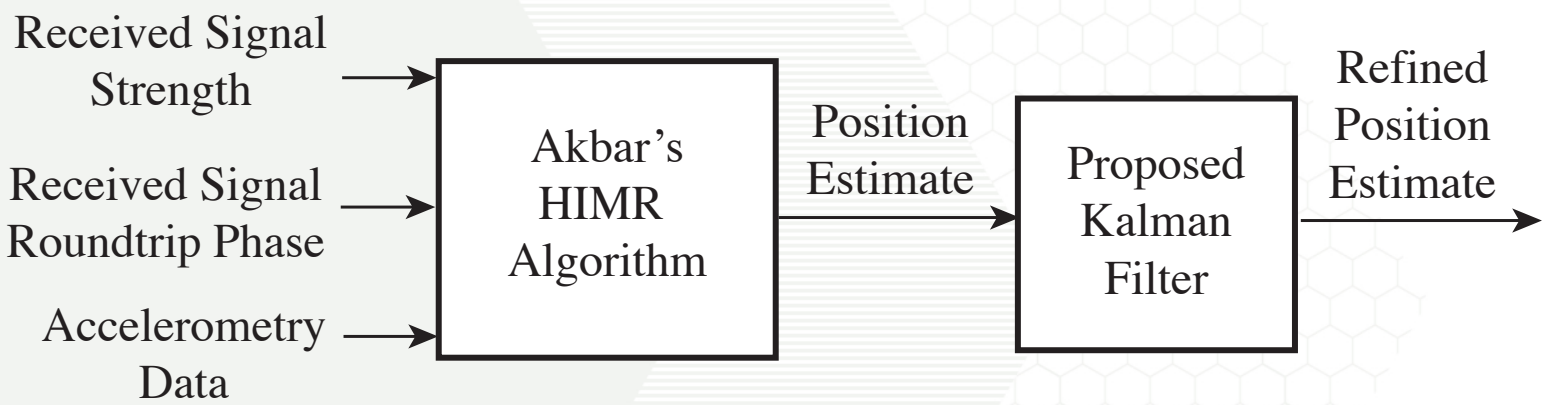

Fig. 3. An overview of how data is processed. RF sensor and physical measurements are converted to noisy estimates of tag position as well as first and second derivatives of position. Then the Kalman filter produces a refined estimate of position as a function of time.

TAG MOTION DYNAMICS-CONTINUOUS TIME

A tagged object moves in one dimension. Its state-space model is:

$$\dot{x}(t) = Ax(t) + Bw(t) \tag{1}$$

$$y(t) = Cx(t) + v(t) \tag{2}$$

Application of Newton's law leads to the coefficient matrices:

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \text{C}= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Expected value of the initial state and initial covariance are:

$$E\{x(0)\} = \hat{x}_0 \tag{4}$$

$$E\{(x(0) - \hat{x}_0)(x(0) - \hat{x}_0)'\} = P_0 \tag{5}$$

The disturbance input and noise input are uncorrelated zero-mean white Gaussian noise with spectral densities Q and R:

$$E\{w(t)w'(\tau)\} = Q\delta(t - \tau) \tag{6}$$

$$E\{v(t)v'(\tau)\} = R\delta(t - \tau) \tag{7}$$

TAG MOTION DYNAMICS-DISCRETE TIME

- Estimation is preferably implemented in discrete-time in a digital processor.
- Suppose the values of the continuous signals at the sampling instants are $x_k = x(kT)$, $w_k = w(kT)$, $y_k = y(kT)$, $v_k = v(kT)$ where T is the sampling period. The discrete time state-space model is:

$$x_{k+1} = Fx_k + Gw_k \tag{8}$$

$$y_k = Hx_k + v_k \tag{9}$$

where $F = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$, G= $\begin{bmatrix} 0 \\ 0 \\ T \end{bmatrix}$, H= $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ (10)

The motion is induced by the finite rectangular-pulse disturbance input w as shown in Figure 4:

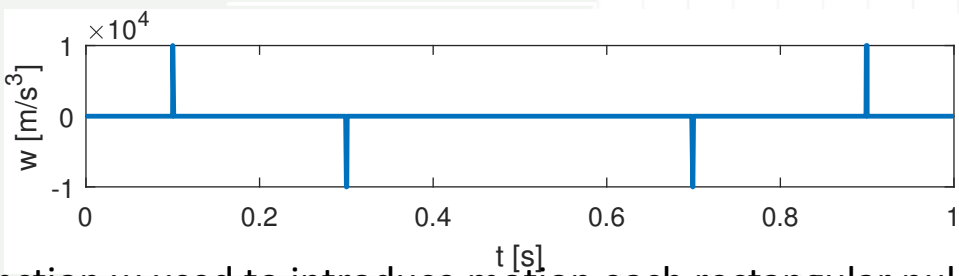

Fig. 4 Forcing function w used to introduce motion each rectangular pulse has a duration of 1ms

TAG MOTION DYNAMICS-DISCRETE TIME

Inferred from the continuous model, the expected value of the initial state and initial covariance are:

$$E\{x_0\} = \hat{x}_0 \tag{11}$$
$$E\{(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)'\} = P_0 \tag{12}$$

Where $\hat{x}_0$ and P_0 come from (4)-(5). The disturbance input and noise input satisfy:

$$E\{w(t)w'(\tau)\} = W \tag{13}$$
$$E\{v(t)v'(\tau)\} = V \tag{14}$$

Assuming small T

$$W \approx Q/T, V \approx R \tag{15}$$

VARIABLE-GAIN KALMAN FILTER 1

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VARIABLE-GAIN KALMAN FILTER 1

Using discrete model (8)-(9), the estimate x_k depend on measurement up through the present value y_k. The time-varying gain is:

$$L_k = P_k^- H'(HP_k^- H' + V)^{-1} \tag{16}$$

A posteriori estate estimate and error covariance are:

$$\hat{x}_k^+ = \hat{x}_k^- - L_k(H\hat{x}_k^- - y_k) \tag{17}$$

$$P_k^+ = (I - L_k H)P_k^- \tag{18}$$

A prior state estimate and error covariance are:

$$\hat{x}_{k+1}^- = F\hat{x}_k^+ \tag{19}$$

$$P_{k+1}^- = FP_k^+ F' + GWG' \tag{20}$$

VARIABLE-GAIN KALMAN FILTER 1

Initialization from (11)-(12)

$$\hat{x}_0^- = \hat{x}_0 \tag{21}$$

$$P_0^- = P_0 \tag{22}$$

The mean square error

$$\epsilon_k = E\{(x_k - \hat{x}_k^+)'(x_k - \hat{x}_k^+)\} \tag{23}$$

At time k, the error is determined by $\hat{x}_0^-$, P_0^- and the gain sequence L_0,…, L_k, influenced by W and V.

By choosing L_k according to (16), (18), and (20), ϵ_k is minimized for every $k \geq 0$.

VARIABLE-GAIN KALMAN FILTER 2

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VARIABLE-GAIN KALMAN FILTER 2

Using discrete model (8)-(9), the estimate x_k depend on measurement up through the present value y_{k-1}. The time-varying gain is:

$$L_k = FP_kH'(HP_kH' + V)^{-1} \tag{24}$$

A estate estimate and error covariance are:

$$\hat{x}_{k+1} = F\hat{x}_k - L_k(H\hat{x}_k - y_k) \tag{25}$$

where $P_{k+1} = (F - L_kH)P_k^+F' + GWG'$ (26)

Initialization from (11)-(12)

$$\hat{x}_0 = \hat{x}_0 \qquad P_0 = P_0 \tag{27}$$

The mean square error $\epsilon_k = E\{(x_k - \hat{x}_k^+)'(x_k - \hat{x}_k^+)\}$ (28)

At time k, the error is determined by $\hat{x}_0^-$, P_0^- and the gain sequence L_0,…, L_k, influenced by W and V.

By choosing L_k according to (24) and (26), ϵ_k is minimized for every $k \geq 0$.

FIXED-GAIN KALMAN FILTER

FOR HIMR RFID SYSTEM

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FIXED-GAIN KALMAN FILTER

Using continuous model (1)-(2), the estimate x_k depend on measurement up through the present value y_{k-1}. The fixed gain is:

$$L = PC'R^{-1} \tag{29}$$

where P satisfies $AP + PA' - PC'R^{-1}CP + BQB' = 0$ (30)

Then we have:

$$\dot{\hat{x}}(t) = A\hat{x}(t) - L\left(C\hat{x}(t) - y(t)\right) \tag{31}$$

$$P_{k+1} = (F - L_k H)P_k^{+}F' + GWG' \tag{32}$$

Initialization from (4) $x(0) = \hat{x}_0$

The mean square error $\epsilon(t) = E\{(x(t) - \hat{x}(t))'(x_k - \hat{x}(t))\}$ (33)

At time t, the error is determined by $\hat{x}_0$ and L which is influced by Q and R. Choosing L according to (27) and (28), ϵ_k is minimized as $k \to \infty$.

Implement on discrete time stamp

$$\hat{x}_{k+1} = \hat{x}_k - \mathrm{T}\left(A\hat{x}_k - L(C\hat{x}_k - y_k)\right) \tag{34}$$

SIMULATION RESULTS

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GENERATE CONTINUOUS AND DISCRETE MEASUREMENT SIGNALS

Continuous-time response of state variables are obtained using (1) with $1\mu s$ time step. Discrete-time measurement from (9) are obtained by using the function randn in Matlab to add sensor noise with sampling period T = 1ms.

$$Q = 10^6, R = \begin{bmatrix} 0.05 & 0 & 0 \\ 0 & 0.1 & 0 \\ 0 & 0 & 1.6 \end{bmatrix}, W = 10^9, V = \begin{bmatrix} 0.05 & 0 & 0 \\ 0 & 0.1 & 0 \\ 0 & 0 & 1.6 \end{bmatrix}, \hat{x}_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, P_0 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

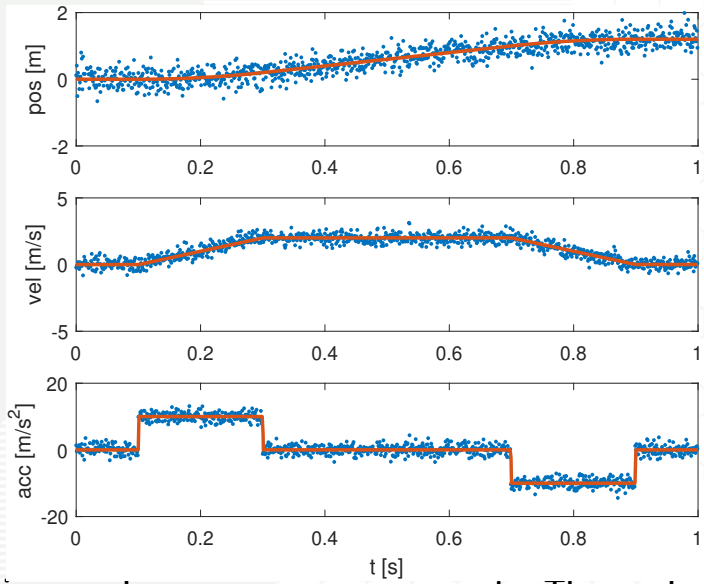

Fig. 5. Simulation of tag motion and sensor measurements. The red solid curve represents the actual motion and the blue dots represent the samples of sensor outputs

ESTIMATION RESULTS COMPARISON

Y_{pos} is the vector of sensed values, X_{pos} is the vector of true values, and $\hat{X}_{pos}$ is the vector of estimated values .

$$E_{est} = X_{pos} - \hat{X}_{pos}$$

RMS error is $E_{rms} = \left(\frac{1}{N}\sum_{n=1}^{N} E^2[n]\right)^{\frac{1}{2}}$ and peak error is: $E_{peak} = max\{|E[1]|, \dots \dots, |E[N]|\}$

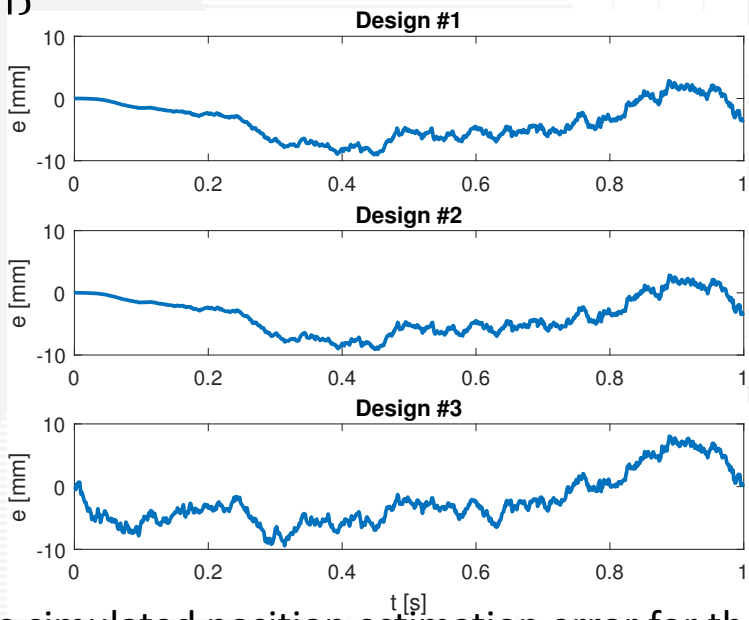

Fig. 6. Comparison of the simulated position estimation error for the three estimator designs

ESTIMATION ACCURACY

- The first table shows the poor sensor accuracy whereas the second table shows the excellent estimator accuracies

- The estimators are 89 times more accurate than the sensors with respect to the peak errors, whereas they are 47 times more accurate with respect to rms errors

TABLE I
POSITION SENSOR PERFORMANCE

$E_{\text{out,peak}}$	800 mm
$E_{\text{out,rms}}$	223 mm

TABLE II
POSITION ESTIMATOR PERFORMANCE

	Design #1	Design #2	Design #3
$E_{\text{est,peak}}$	9.05 mm	9.07 mm	9.42 mm
$E_{\text{est,rms}}$	4.74 mm	4.75 mm	4.66 mm

CONCLUSION

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CONCLUSION

- The addition of a Kalman filter to the original HIMR algorithm reduces estimation errors of motion variables to around 5mm rms.
- The fixed-gain version of Kalman filter is more computationally efficient than the variable-gain version in usage, yet has similar performance.

Thank you!