## Student Name:

Useful formulas and notation given on last page.

## Midterm Exam 2, EE 527, Spring 2008 (Out of 40 points)

1. We have learnt that the Kalman gain, $K_{t}$, is given by

$$
K_{t} \triangleq \Sigma_{t \mid t-1} H^{T}\left(H \Sigma_{t \mid t-1} H^{T}+R\right)^{-1}
$$

and the filtering error covariance $\Sigma_{t \mid t} \triangleq\left[I-K_{t} H\right] \Sigma_{t \mid t-1}$.
(a) Show that $K_{t}$ can also be rewritten as

$$
K_{t}=\left(\Sigma_{t \mid t-1}^{-1}+H^{T} R^{-1} H\right)^{-1} H^{T} R^{-1}
$$

(b) Use this to show that $\Sigma_{t \mid t}$ can be rewritten as $\Sigma_{t \mid t}=\left(\Sigma_{t \mid t-1}^{-1}+H^{T} R^{-1} H\right)^{-1}$. $8+2$ points
2. Consider a state space model of the form

$$
\begin{aligned}
Y_{t} & =H_{t} X_{t}+r\left(Y_{1}, Y_{2}, \ldots Y_{t-1}\right)+V_{t}, \quad V_{t} \sim \mathcal{N}(0, R) \\
X_{t+1} & =F_{t} X_{t}+q\left(Y_{1}, Y_{2}, \ldots Y_{t}\right)+G U_{t}, \quad U_{t} \sim \mathcal{N}(0, Q)
\end{aligned}
$$

with $X_{0} \sim \mathcal{N}\left(0, \Sigma_{0}\right) . X_{0},\left\{U_{t}, t=0, \ldots \infty\right\},\left\{V_{t}, t=0, \ldots \infty\right\}$ are mutually independent.
(a) The above is a Kalman model, but with a nonzero "feedback control" input in both equations. Derive the Kalman recursion for it, both prediction and update steps.
(b) Now consider the following nonlinear state space model

$$
\begin{aligned}
Y_{t} & =h\left(X_{t}\right)+V_{t}, V_{t} \sim \mathcal{N}(0, R) \\
X_{t+1} & =f\left(X_{t}\right)+G U_{t}, U_{t} \sim \mathcal{N}(0, Q)
\end{aligned}
$$

$X_{0} \sim \mathcal{N}\left(0, \Sigma_{0}\right) . X_{0},\left\{U_{t}, t=0, \ldots \infty\right\},\left\{V_{t}, t=0, \ldots \infty\right\}$ are mutually independent. Linearize $h\left(X_{t}\right)$ about $\hat{X}_{t \mid t-1}$ and linearize $f\left(X_{t}\right)$ about $\hat{X}_{t \mid t}$. Assume the linearized model to be the true one and apply the Kalman filter derived above. This gives the extended Kalman filter for the nonlinear model.
$5+5=10$ points
3. Consider the Kalman model but with $U_{t}, V_{t}$ correlated for the same $t$, i.e.

$$
\begin{aligned}
Y_{t} & =H X_{t}+V_{t}, \quad V_{t} \sim \mathcal{N}(0, R) \\
X_{t+1} & =F X_{t}+G U_{t}, \quad U_{t} \sim \mathcal{N}(0, Q)
\end{aligned}
$$

where $X_{0} \sim \mathcal{N}\left(0, \Sigma_{0}\right)$ and $X_{0},\left\{U_{t}, t=0, \ldots \infty\right\}$ are mutually independent; $\left\{V_{t}, t=0, \ldots \infty\right\}$ are mutually independent; and $U_{t}$ is independent of $V_{\tau}, \tau=1, \ldots t-1$ and of $V_{\tau}, \tau=t+1, \ldots \infty$ But $U_{t}, V_{t}$ are correlated with covariance, $E\left[U_{t} V_{t}^{T}\right]=C$.
(a) Derive the expression for $\hat{X}_{t+1 \mid t}$ in terms of $\hat{X}_{t \mid t}, \hat{X}_{t \mid t-1}, \Sigma_{t \mid t}$ and the known matrices.
(b) Derive the expression for $\Sigma_{t+1 \mid t}$ in terms of $\Sigma_{t \mid t}, \Sigma_{t \mid t-1}$ and the the known matrices.
$7+3=10$ points
4. You are given a sequence of observations $Y_{0}, Y_{2}, \ldots Y_{N-1}$ which satisfy

$$
Y_{n}=X r^{n}+w_{n}, w_{n} \sim \mathcal{N}\left(0, \sigma^{2}\right)
$$

with $X \sim \mathcal{N}\left(0, \sigma_{x}^{2}\right) . X,\left\{w_{n}, n=0, \ldots N-1\right\}$ are mutually independent. $r$ is a constant.
(a) Use the joint Gaussian formula to find the MMSE estimate of $X$ given $Y_{0}, Y_{1}, \ldots Y_{N-1}$.
(b) Can you find the MAP estimate?
$9+1=10$ points

## Formulas

1. Matrix Inversion Identity

$$
(A+B C D)^{-1}=A^{-1}-A^{-1} B\left(C^{-1}+D A^{-1} B\right)^{-1} D A^{-1}
$$

2. For jointly Gaussian $X, Y$ with joint PDF

$$
\begin{aligned}
{\left[\begin{array}{c}
Y \\
X
\end{array}\right] } & \sim \mathcal{N}\left(\left[\begin{array}{c}
\mu_{Y} \\
\mu_{X}
\end{array}\right],\left[\begin{array}{cc}
\Sigma_{Y} & \Sigma_{Y X} \\
\Sigma_{X Y} & \Sigma_{X}
\end{array}\right]\right) \\
E[X \mid Y] & =\mu_{X}+\Sigma_{X Y} \Sigma_{Y}^{-1}\left(Y-\mu_{Y}\right) \\
\operatorname{Cov}[X \mid Y] & =\Sigma_{X}-\Sigma_{X Y} \Sigma_{Y}^{-1} \Sigma_{X}, \\
\text { Note } \operatorname{Cov}[X \mid Y] & \triangleq E\left[(X-E[X \mid Y])(X-E[X \mid Y])^{T} \mid Y\right]
\end{aligned}
$$

3. Kalman filter equations. For the state space model,

$$
\begin{aligned}
Y_{t} & =H_{t} X_{t}+V_{t}, V_{t} \sim \mathcal{N}(0, R) \\
X_{t+1} & =F_{t} X_{t}+G_{t} U_{t}, U_{t} \sim \mathcal{N}(0, Q)
\end{aligned}
$$

where $X_{0},\left\{U_{t}, t=1, \ldots \infty\right\},\left\{V_{t}, t=1, \ldots \infty\right\}$ are mutually independent and $X_{0} \sim \mathcal{N}\left(0, \Sigma_{0}\right)$, we have

$$
\begin{aligned}
K_{t} & =\Sigma_{t \mid t-1} H_{t}^{T}\left(H_{t} \Sigma_{t \mid t-1} H_{t}^{T}+R\right)^{-1} \\
\hat{X}_{t \mid t} & =\hat{X}_{t \mid t-1}+K_{t}\left(Y_{t}-H_{t} \hat{X}_{t \mid t-1}\right) \\
\Sigma_{t \mid t} & =\left[I-K_{t} H_{t}\right] \Sigma_{t \mid t-1} \\
\hat{X}_{t+1 \mid t} & =F_{t} \hat{X}_{t \mid t} \\
\Sigma_{t+1 \mid t} & =F_{t} \Sigma_{t \mid t} F_{t}^{T}+G_{t} Q G_{t}^{T}
\end{aligned}
$$

with initialization, $\hat{X}_{0 \mid-1}=0, \Sigma_{0 \mid-1}=\Sigma_{0}$. Here

$$
\begin{aligned}
\hat{X}_{t \mid s} & \triangleq E\left[X_{t} \mid Y_{1: s}\right] \\
\Sigma_{t \mid s} & \triangleq \operatorname{Cov}\left[X_{t} \mid Y_{1: s}\right]
\end{aligned}
$$

