# 6.241 Spring 2011 

Midterm Exam

March 27, 2011

## Problem 1

Let $A \in \mathbb{C}^{n \times n}$, and $B \in \mathbb{C}^{m \times m}$. Show that $X(t)=e^{A t} X(0) e^{B t}$ is the solution to $\dot{X}=$ $A X+X B$.

Solution - Recalling the definition of matrix exponential, $e^{A t}=\sum_{i=0}^{\infty} \frac{1}{i!}(A t)^{i}$, it is clear that, for any matrix $A, e^{A t}=I$ for $t=0$, and $d e^{A t} / d t=A e^{A t}=e^{A t} A$.

Hence,

$$
\begin{aligned}
\frac{d}{d t}\left(e^{A t} X(0) e^{B t}\right)=\left(\frac{d}{d t} e^{A t}\right) X(0) e^{B t}+e^{A t} & \left(\frac{d}{d t} X(0)\right) e^{B t}+e^{A t} X(0)\left(\frac{d}{d t} e^{B t}\right) \\
& =A\left(e^{A t} X(0) e^{B t}\right)+0+\left(e^{A t} X(0) e^{B t}\right) B .
\end{aligned}
$$

Furthermore, for $t=0$,

$$
\left.\left(e^{A t} X(0) e^{B t}\right)\right|_{t=0}=X(0) .
$$

Hence we can conclude that the proposed function is in fact the solution to the initialvalue problem under consideration.

## Problem 2

Given two non-zero vectors $v, w \in \mathbb{R}^{n}$. Does there exist a matrix $A$ such that $v=A w$ and

1. $\sigma_{\max }(A)=\sqrt{v^{T} v / w^{T} w}$ ?
2. $\|A\|_{1}=\|v\|_{\infty} /\|w\|_{\infty}$ ?

Prove or disprove each case separately.
Solution - We have two cases:

1. The rank-one matrix $A=\frac{1}{w^{T} w} v w^{T}$ has the required properties. Direct substitution shows that this matrix satisfies the condition $v=A w$. Moreover, the only non-zero eigenvalue of the (rank-one) matrix $A^{T} A=\frac{1}{\left(w^{T} w\right)^{2}} w v^{T} v w^{T}=\frac{v^{T} v}{\left(w^{T} w\right)^{2}} w w^{T}$ is equal to $\lambda_{\max }\left(A^{T} A\right)=v^{T} v / w^{T} w$, from which we get $\sigma_{\max }(A)=\sqrt{\lambda_{\max }\left(A^{T} A\right)}=\sqrt{v^{T} v / w^{T} w}$.
2. There is no such matrix in general. Consider the following counter-example. Pick, e.g., $v=(1,1)$, and $w=(1,0)$. The matrix $A$ must be such that all elements in its first column are equal to 1 , and hence $\|A\|_{1} \geq 2>\|v\|_{\infty} /\|w\|_{\infty}=1$.

## Problem 3

Use the projection theorem to solve the problem:

$$
\min _{x \in \mathbb{R}^{n}}\left\{x^{T} Q x: A x=b\right\}
$$

where $Q$ is a positive-definite $n \times n$ matrix, $A$ is a $m \times n$ real matrix, with rank $m<n$, and $b$ is a real $m$-dimensional vector. Is the solution unique?

Solution - (Note that $Q$ being positive-definite implies it is self-adjoint, i.e., Hermitian.) Let $x_{0}$ be such that $A x_{0}=b$, and consider the change of variables $z=x-x_{0}$. In the inner product space $\mathbb{R}^{n}$, with inner product $\langle u, v\rangle=u^{T} Q v$, it is desired to minimize $\|x\|^{2}=x^{T} Q x=\left\|z+x_{0}\right\|^{2}$, subject to the constraint that $z$ lies in the subspace $M:=\left\{z \in \mathbb{R}^{n}: A z=0\right\}$. Using the projection theorem, we know that an optimal solution $\hat{z}=\hat{x}-x_{0}$ must be such that $\left(\hat{z}+x_{0}=\hat{x}\right) \perp M$, i.e., $\langle\hat{x}, y\rangle=\hat{x}^{T} Q y=0$, for all $y \in M$. Summarizing, we know that

$$
\begin{aligned}
\hat{x}^{T} Q y & =0, \quad \forall A y=0 \\
A x & =b .
\end{aligned}
$$

In order to satisfy the first equation for all $y$ such that $A y=0, \hat{x}$ must be of the form $\hat{x}=Q^{-1} A^{T} v$, for some $v \in \mathbb{R}^{m}$. The vector $v$ can be found using the constraint $A x=b$, i.e.,

$$
A \hat{x}=A Q^{-1} A^{T} v=b,
$$

and hence

$$
v=\left(A Q^{-1} A^{T}\right)^{-1} b
$$

Concluding,

$$
\hat{x}=Q^{-1} A^{T}\left(A Q^{-1} A^{T}\right)^{-1} b .
$$

## Problem 4

Let $\|A\|<1$. Show that $\left\|(I-A)^{-1}\right\| \geq \frac{1}{1+\|A\|}$.
Solution-First of all, for any vector $x_{0}$, with $\left\|x_{0}\right\|=1$,

$$
\left\|(I-A) x_{0}\right\| \geq\left\|x_{0}\right\|-\left\|A x_{0}\right\| \geq 1-\|A\|>0
$$

which shows that the matrix $I-A$ is invertible, i.e., there is no vector $x_{0}$, with $\left\|x_{0}\right\|=1$, such that $(I-A) x_{0}=0$.

Furthermore, the following chain of inequalities holds:

$$
\begin{aligned}
1=\|I\|=\left\|(I-A)(I-A)^{-1}\right\| & \leq\|I-A\| \cdot\left\|(I-A)^{-1}\right\| \\
& \leq(\|I\|+\|A\|) \cdot\left\|(I-A)^{-1}\right\|=(1+\|A\|) \cdot\left\|(I-A)^{-1}\right\|,
\end{aligned}
$$

and the result follows. The definition of induced norm implies that $\|I\|=1$. The first inequality is due to the submultiplicative property of induced norms. The second inequality can be derived from the triangle inequality.

## Problem 5

Consider a single-input discrete-time LTI system, described by

$$
\begin{gathered}
x[k+1]=\left[\begin{array}{ll}
1 & 1 \\
0 & 1
\end{array}\right] x[k]+\left[\begin{array}{l}
0 \\
1
\end{array}\right] u[k] \\
y[k]=x[k]
\end{gathered}
$$

and the initial condition $x[0]=0$. Given $M>1$, what is the maximum value of $\|y[M]\|_{2}$ that can be attained with an input of "unit energy,", i.e., such that $u[0]^{2}+u[2]^{2}+\ldots+$ $u[M-1]^{2}=1$ ? What is the input that attains such value? How would your answer change if you were to double $M$, i.e., $M \leftarrow 2 M$ ?

You can solve this problem symbolically; if you want to get numerical results, it is suggested you use matlab or similar program.

Solution - Let us define

$$
A=\left[\begin{array}{ll}
1 & 1 \\
0 & 1
\end{array}\right], \quad B=\left[\begin{array}{l}
0 \\
1
\end{array}\right]
$$

Then,

$$
\begin{aligned}
y[1]=x[1] & =A x[0]+B u[0]=B u[0], \\
y[2]=x[2] & =A x[1]+B u[1]=A B u[0]+B u[1], \\
& \cdots \\
y[M]=x[M] & =A x[M-1]+B u[M-1]=A^{M-1} B u[0]+A^{M-2} B u[1]+\ldots+B u[M-1],
\end{aligned}
$$

which can be written as

$$
y[M]=\left[\begin{array}{llll}
A^{M-1} B & A^{M-2} B & \ldots & B
\end{array}\right]\left[\begin{array}{c}
u[0] \\
u[1] \\
\ldots \\
u[M-1]
\end{array}\right]=\Gamma_{M} U_{M},
$$

where

$$
\Gamma_{M}=\left[\begin{array}{llll}
A^{M-1} B & A^{M-2} B & \ldots & B
\end{array}\right],
$$

and

$$
U_{M}=\left[\begin{array}{llll}
u[0] & u[1] & \ldots & u[M-1]
\end{array}\right]^{T} .
$$

The solution of the problem

$$
\begin{array}{cl}
\max _{U_{M}} & \|y[M]\|_{2}=\left\|\Gamma_{M} U_{M}\right\|_{2} \\
\text { s.t. } & \left\|U_{M}\right\|_{2}=1
\end{array}
$$

is given by $\sigma_{\max }\left(\Gamma_{M}\right)$, and is attained for $U_{M}=w_{\max }\left(\Gamma_{M}\right)$, where $w_{\max }$ refers to the (right) singular vector associated with the maximum singular value.

Numerically, e.g., for $M=4, \sigma_{\max }\left(\Gamma_{4}\right)=4.1, U_{M}=\left[\begin{array}{llll}0.7661 & 0.5452 & 0.3243 & 0.1035\end{array}\right]$, and $y[4]=\left[\begin{array}{ll}3.7129 & 1.7391\end{array}\right]$.

The output after $2 M$ steps can be written as

$$
y[2 M]=A^{M} \Gamma_{M} U_{M}^{\prime}+\Gamma_{M} U_{M}^{\prime \prime}=\Gamma_{2 M} U_{2 M},
$$

where the matrix $\Gamma_{2 M}$ is defined as

$$
\Gamma_{2 M}=\left[\begin{array}{ll}
A^{M} \Gamma_{M} & \Gamma_{M}
\end{array}\right] .
$$

Clearly, $\sigma_{\max }\left(\Gamma_{2 M}\right) \geq \sigma_{\max }\left(\Gamma_{M}\right)$, i.e., $\|y[2 M]\|_{2}$ can be made at least as large as $\|y[M]\|_{2}$, e.g., by concentrating the energy of the input in the last M steps (and setting the previous ones to zero).

## Problem 6

Consider a physical system whose behavior is modeled, in continuous time, by the differential equation

$$
\dot{x}=A x+B u .
$$

Assume that you have two sensors. The first sensor yields measurements $y_{1}=C_{1} x$ for $t=0,1,2,3, \ldots$, and the second sensor yields measurements $y_{2}=C_{2} x$ for $t=0,2,4, \ldots$. Assuming that $u(t)=u(\lfloor t\rfloor)$, for all $t \geq 0$, derive a discrete-time state-space model for the system.

Solution - This is a sample-and-hold system, commonly used as a model for computercontrolled systems. In this particular model, the two sensors have different sampling rate. Even though the system is not time invariant, the sampling strategy is periodic-and we can find a time-invariant model for the system exploiting this periodicity.

Consider the following expression for the response of a continuous-time LTI system.

$$
x\left(t_{1}\right)=e^{A\left(t_{1}-t_{0}\right)} x\left(t_{0}\right)+\int_{t_{0}}^{t_{1}} e^{A\left(t_{1}-\tau\right)} B u(\tau) d \tau ;
$$

In particular, if $t_{0}$ is an integer, and $t_{1}=t_{0}+1$,

$$
x\left(t_{0}+1\right)=e^{A} x\left(t_{0}\right)+\int_{0}^{1} e^{A(1-\tau)} B u\left(t_{0}\right) d \tau=A_{\mathrm{d}} x\left(t_{0}\right)+B_{\mathrm{d}} u\left(t_{0}\right),
$$

where $A_{\mathrm{d}}=e^{A}$, and $B_{\mathrm{d}}=\left(\int_{0}^{1} e^{A(1-\tau)} d \tau\right) B$.
Define the output signal for the discrete-time model as

$$
y_{\mathrm{d}}[k]=\left[\begin{array}{c}
y_{1}(2 k-1) \\
y_{1}(2 k) \\
y_{2}(2 k)
\end{array}\right] .
$$

Similarly, define the input signal for the discrete-time model as

$$
u_{\mathrm{d}}[k]=\left[\begin{array}{c}
u(2 k-1) \\
u(2 k)
\end{array}\right] .
$$

Finally, define the state vector as

$$
x_{\mathrm{d}}[k]=x(2 k-1) .
$$

With these definitions in mind, one can write that

$$
\begin{aligned}
y(2 k-1) & =x(2 k-1) \\
y(2 k) & =x(2 k)=A_{\mathrm{d}} x(2 k-1)+B_{\mathrm{d}} u(2 k-1) \\
x(2 k+1) & =A_{\mathrm{d}}^{2} x(2 k-1)+A_{\mathrm{d}} B_{\mathrm{d}} u(2 k-1)+B_{\mathrm{d}} u(2 k)
\end{aligned}
$$

The desired state-space model is as follows:

$$
\begin{aligned}
x_{\mathrm{d}}[k+1] & =A_{\mathrm{d}}^{2} x_{\mathrm{d}}[k]+\left[\begin{array}{ll}
A_{\mathrm{d}} B_{\mathrm{d}} & \left.B_{\mathrm{d}}\right] u[k] \\
y_{\mathrm{d}}[k] & =\left[\begin{array}{c}
C_{1} \\
C_{1} A_{\mathrm{d}} \\
C_{2} A_{\mathrm{d}}
\end{array}\right] x_{\mathrm{d}}[k]+\left[\begin{array}{cc}
0 & 0 \\
C_{1} B_{\mathrm{d}} & 0 \\
C_{2} B_{\mathrm{d}} & 0
\end{array}\right] u_{\mathrm{d}}[k] .
\end{array} . . \begin{array}{l}
\end{array} .\right.
\end{aligned}
$$

Notice that this model is time-invariant, but is no longer strictly causal, since $D \neq 0$.

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