# Matrix Inverse and Condition 

Berlin Chen<br>Department of Computer Science \& Information Engineering<br>National Taiwan Normal University

Reference:

1. Applied Numerical Methods with MATLAB for Engineers, Chapter 11 \& Teaching material

## Chapter Objectives

- Knowing how to determine the matrix inverse in an efficient manner based on $L U$ factorization
- Understanding how the matrix inverse can be used to assess stimulus-response characteristics of engineering systems
- Understanding the meaning of matrix and vector norms and how they are computed
- Knowing how to use norms to compute the matrix condition number
- Understanding how the magnitude of the condition number can be used to estimate the precision of solutions of linear algebraic equations


## Matrix Inverse (1/4)

- Recall that if a matrix $[A]$ is square, there would be another matrix $[A]^{-1}$, called the inverse of $[A]$, for which $[A][A]^{-1}=[A]^{-1}[A]=[I]$ ( $[1]$ : identity matrix)
- The inverse can be computed in a column by column fashion by generating solutions with unit vectors as the right-hand-side constants:
- A three-variable system

$$
\begin{gathered}
{[A]\left\{x_{1}\right\}=\left\{\begin{array}{l}
1 \\
0 \\
0
\end{array}\right\} \quad[A]\left\{x_{2}\right\}=\left\{\begin{array}{l}
0 \\
1 \\
0
\end{array}\right\} \quad[A]\left\{x_{3}\right\}=\left\{\begin{array}{l}
0 \\
0 \\
1
\end{array}\right\}} \\
{[A]^{-1}=\left[\begin{array}{lll}
x_{1} & x_{2} & x_{3}
\end{array}\right]}
\end{gathered}
$$

## Matrix Inverse (2/4)

- Recall that $L U$ factorization can be used to efficiently evaluate a system for multiple right-hand-side vectors thus, it is ideal for evaluating the multiple unit vectors needed to compute the inverse



## Matrix Inverse (3/4)

Example 11.1
Problem Statement. Employ $L U$ factorization to determine the matrix inverse for the system from Example 10.1:

$$
[A]=\left[\begin{array}{ccc}
3 & -0.1 & -0.2 \\
0.1 & 7 & -0.3 \\
0.3 & -0.2 & 10
\end{array}\right]
$$

Recall that the factorization resulted in the following lower and upper triangular matrices:

$$
[U]=\left[\begin{array}{ccc}
3 & -0.1 & -0.2 \\
0 & 7.00333 & -0.293333 \\
0 & 0 & 10.0120
\end{array}\right] \quad[L]=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0.0333333 & 1 & 0 \\
0.100000 & -0.0271300 & 1
\end{array}\right]
$$

Solution. The first column of the matrix inverse can be determined by performing the forward-substitution solution procedure with a unit vector (with 1 in the first row) as the right-hand-side vector. Thus, the lower triangular system can be set up as (recall Eq. [10.8])

$$
\left[\begin{array}{ccc}
1 & 0 & 0 \\
0.0333333 & 1 & 0 \\
0.100000 & -0.0271300 & 1
\end{array}\right]\left\{\begin{array}{l}
d_{1} \\
d_{2} \\
d_{3}
\end{array}\right\}=\left\{\begin{array}{l}
1 \\
0 \\
0
\end{array}\right\}
$$

and solved with forward substitution for $\{d\}^{T}=\left[\begin{array}{lll}1 & -0.03333 & -0.1009\end{array}\right]$. This vector can then be used as the right-hand side of the upper triangular system (recall Eq. [10.3]):

$$
\left[\begin{array}{ccc}
3 & -0.1 & -0.2 \\
0 & 7.00333 & -0.293333 \\
0 & 0 & 10.0120
\end{array}\right]\left\{\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right\}=\left\{\begin{array}{c}
1 \\
-0.03333 \\
-0.1009
\end{array}\right\}
$$

which can be solved by back substitution for $\{x\}^{T}=\left[\begin{array}{lll}0.33249 & -0.00518 & -0.01008\end{array}\right]$, which is the first column of the matrix inverse:

$$
[A]^{-1}=\left[\begin{array}{ccc}
0.33249 & 0 & 0 \\
-0.00518 & 0 & 0 \\
-0.01008 & 0 & 0
\end{array}\right]
$$

## Matrix Inverse (4/4)

## Example 11.1

To determine the second column, Eq. (10.8) is formulated as

$$
\left[\begin{array}{ccc}
1 & 0 & 0 \\
0.0333333 & 1 & 0 \\
0.100000 & -0.0271300 & 1
\end{array}\right]\left\{\begin{array}{l}
d_{1} \\
d_{2} \\
d_{3}
\end{array}\right\}=\left\{\begin{array}{l}
0 \\
1 \\
0
\end{array}\right\}
$$

This can be solved for $\{d\}$, and the results are used with Eq. (10.3) to determine $\{x\}^{T}=$ $\lfloor 0.004944 \quad 0.1429030 .00271\rfloor$, which is the second column of the matrix inverse:

$$
[A]^{-1}=\left[\begin{array}{rrr}
0.33249 & 0.004944 & 0 \\
-0.00518 & 0.142903 & 0 \\
-0.01008 & 0.002710 & 0
\end{array}\right]
$$

Finally, the same procedures can be implemented with $\{b\}^{T}=\left[\begin{array}{lll}0 & 0 & 1\end{array}\right]$ to solve for $\{x\}^{T}=\left\lfloor\begin{array}{lll}0.006798 & 0.004183 & 0.09988 \\ \hline\end{array}\right.$, which is the final column of the matrix inverse:

$$
[A]^{-1}=\left[\begin{array}{rrr}
0.33249 & 0.004944 & 0.006798 \\
-0.00518 & 0.142903 & 0.004183 \\
-0.01008 & 0.002710 & 0.099880
\end{array}\right]
$$

The validity of this result can be checked by verifying that $[A][A]^{-1}=[I]$.

## Stimulus-Response Computations (1/3)

- Many systems can be modeled as a linear combination of equations, and thus written as a matrix equation:

$$
[\text { Interactions }]\{\text { response }\}=\{\text { stimuli }\}
$$

- The system response can thus be found using the matrix inverse


## Stimulus-Response Computations (2/3)

- Example: Three Bungee Jumpers


FIGURE 8.1
Three individuals connected by bungee cords,

compute the displacement of each

FIGURE 8.2
Free-body diagrams.
of the jumpers when
coming to the equilibrium positions
$m_{1} \frac{d^{2} x_{1}}{d t^{2}}=m_{1} g+k_{2}\left(x_{2}-x_{1}\right)-k_{1} x_{1}$


## Stimulus-Response Computations (3/3)

- The matrix inverse provides a powerful technique for understanding the interrelationships of component parts of complicated systems

$$
\begin{aligned}
& {[A]\{x\}=\{b\} } \\
\Rightarrow & \{x\}=[A]^{-1}\{b\}
\end{aligned}
$$

or

$$
\begin{aligned}
& x_{1}=a_{11}^{-1} b_{1}+a_{12}^{-1} b_{2}+a_{13}^{-1} b_{3} \\
& x_{2}=a_{21}^{-1} b_{1}+a_{22}^{-1} b_{2}+a_{23}^{-1} b_{3} \\
& x_{3}=a_{31}^{-1} b_{1}+a_{32}^{-1} b_{2}+a_{33}^{-1} b_{3}
\end{aligned}
$$

Each of its element $a_{i j}^{-1}$ represents the response of a single part of the system to a unit stimulus of any other part of the system.
where

$$
[A]^{-1}=\left[\begin{array}{lll}
a_{11}^{-1} & a_{12}^{-1} & a_{13}^{-1} \\
a_{21}^{-1} & a_{22}^{-1} & a_{22}^{-1} \\
a_{31}^{-1} & a_{32}^{-1} & a_{33}^{-1}
\end{array}\right]
$$

> Element $a_{i j}^{-1}$ of the matrix inverse represents, for example, the force in member $i$ due to a unit external force at node $j$.

## III-Conditioned Systems

- Three direct methods for discerning whether systems are ill-conditioned

1. Scale the matrix of coefficients [A] so that the largest element in each row is 1 . Invert the scaled matrix and if there are elements of $[\mathrm{A}]^{-1}$ that are several orders of magnitude greater than one, it is likely that the system is ill-conditioned
2. Multiply the inverse $[A]^{-1}$ by the original coefficient matrix $[A]$ and assess whether the result is close to the identity matrix [I], If not, it indicates ill-conditioning
3. Invert the inverted matrix and assess whether the result is sufficiently close to the original coefficient matrix. If not, it indicates ill-conditioning

- Can we obtain a single number serving as an indicator of illconditioned systems?


## Vector and Matrix Norms

- A norm is a real-valued function that provides a measure of the size or "length" of multi-component mathematical entities such as vectors and matrices
- Vector norms and matrix norms may be computed differently


## Vector Norms

- For a vector $\{X\}$ of size $n$, the $p$-norm is:

$$
\|X\|_{p}=\left(\sum_{i=1}^{n}\left|x_{i}\right|^{p}\right)^{1 / p}
$$

- Important examples of vector $p$-norms include:

$$
\begin{array}{ll}
p=1: \text { sum of the absolute values } & \|X\|_{1}=\sum_{i=1}^{n}\left|x_{i}\right| \\
p=2: \text { Euclidian norm (length) } & \|X\|_{2}=\|X\|_{e}=\sqrt{\sum_{i=1}^{n} x_{i}^{2}} \\
p=\infty: \text { maximum - magnitude } & \|X\|_{\infty}=\max _{1 \leq i \leq n}\left|x_{i}\right|
\end{array}
$$

## Matrix Norms

- Common matrix norms for a matrix $[A]$ include:

$$
\begin{array}{ll}
\text { column-sum norm } & \|A\|_{1}=\max _{1 \leq j \leq n} \sum_{i=1}^{n}\left|a_{i j}\right| \\
\text { Frobenius norm } & \|A\|_{f}=\sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} a_{i j}^{2}} \\
\text { row - sum norm } & \|A\|_{\infty}=\max _{1 \leq i \leq n} \sum_{j=1}^{n}\left|a_{i j}\right| \\
\text { spectral norm (2 norm) } & \|A\|_{2}=\left(\mu_{\max }\right)^{1 / 2}
\end{array}
$$

- Note: $\mu_{\max }$ is the largest eigenvalue of $[A]^{\top}[A]$


## Matrix Condition Number

- The matrix condition number Cond $[A]$ is obtained by calculating Cond $[A]=\|A\| \cdot\left\|A^{-1}\right\|$
- In can be shown that:

Ralston \& Rabinowitz, 1978

$$
\frac{\|\Delta X\|}{\|X\|} \leq \operatorname{Cond}[A] \frac{\|\Delta A\|}{\|A\|}
$$

$$
\text { given that }[A]\{x\}=\{b\}
$$

- The relative error of the norm of the computed solution can be as large as the relative error of the norm of the coefficients of $[A]$ multiplied by the condition number
- If the coefficients of $[A]$ are known to $t$ digit precision (rounding errors are on the order of $10^{-t}$ ), the solution $[X]$ may be valid to only $t-\log _{10}(\operatorname{Cond}[A])$ digits
- If the conditional number is much greater than 1 , it is suggested that the system is prone to being ill-conditioned


## MATLAB Commands (1/3)

- MATLAB has built-in functions to compute both norms and condition numbers:
- norm ( $X, p$ )
- Compute the $p$ norm of vector $X$, where $p$ can be any number, inf, or 'fro' (for the Euclidean norm)
- $\operatorname{norm}(A, p)$
- Compute a norm of matrix $A$, where $p$ can be 1,2 , inf, or 'fro' (for the Frobenius norm)
- cond ( $X, p$ ) or cond ( $A, p$ )
- Calculate the condition number of vector $X$ or matrix $A$ using the norm specified by $p$


## MATLAB Commands (2/3)

## Example 11.4

Problem Statement. Use MATLAB to evaluate both the norms and condition numbers for the scaled Hilbert matrix previously analyzed in Example 11.3:

$$
[A]=\left[\begin{array}{lll}
1 & \frac{1}{2} & \frac{1}{3} \\
1 & \frac{2}{3} & \frac{1}{2} \\
1 & \frac{3}{4} & \frac{3}{5}
\end{array}\right]
$$

(a) As in Example 11.3, first compute the row-sum versions ( $p=$ inf ). (b) Also compute the Frobenius $(p=$ 'fro') and the spectral $(p=2)$ condition numbers.

Solution: (a) First, enter the matrix:

```
>> A = [1 1/2 1/3;1 2/3 1/2;1 3/4 3/5];
```

Then, the row-sum norm and condition number can be computed as

```
>> norm(A,inf)
ans =
    2.3500
>> cond(A,inf)
ans =
    \| A \| \| \infty = ~ \operatorname { m a x } _ { 1 \leq i \leq n } \sum _ { j = 1 } ^ { n } \| a _ { i j } \|
    451.2000
```


## MATLAB Commands (3/3)

## Example 11.4

(b) The condition numbers based on the Frobenius and spectral norms are

```
>> cond(A,'fro')
ans =
|A\mp@subsup{|}{f}{}=\sqrt{}{\mp@subsup{\sum}{i=1}{n}\mp@subsup{\sum}{j=1}{n}\mp@subsup{a}{ij}{2}}
>> cond(A)
ans \(=\)
\[
\|A\|_{2}=\left(\mu_{\max }\right)^{1 / 2}
\]
```

366.3503

