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CS383C Numerical Analysis

Midterm Exam

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Exercise 1.

(a) Prove that $\|\cdot\|$ is a vector norm.

To prove $||\cdot||$ is a vector norm, we have to show all the following three property holds:

- If $x \neq 0$, then ||x|| > 0.
- For arbitrary scalar α and vector x, $||\alpha x|| = |\alpha| \cdot ||x||$.
- For arbitrary vector x and y, $||x + y|| \le ||x|| + ||y||$.

Now we turn to prove each of them individually.

Proof. Since D is diagonal with positive diagonal elements, then $\forall i, \ \delta_i > 0$ holds. Besides, since $x \neq 0$, then $\exists i, \ x_i^2 > 0$.

$$||x|| = \sqrt{x^T Dx} = \sqrt{\sum_{i=0}^{m-1} \delta_i x_i^2} > 0$$
 $x \neq 0$ (1)

Therefore, we proved that if $x \neq 0$, then ||x|| > 0.

Proof.

$$||\alpha x|| = \sqrt{(\alpha x)^T D(\alpha x)} = \sqrt{\sum_{i=0}^{m-1} \alpha^2 \delta_i x_i^2} = \sqrt{\alpha^2 \sum_{i=0}^{m-1} \delta_i x_i^2} = |\alpha| \sqrt{\sum_{i=0}^{m-1} \delta_i x_i^2} = |\alpha| \cdot ||x||$$
 (2)

Proof.

$$||x+y||^2 = (\sqrt{(x+y)^T D(x+y)})^2 = x^T Dx + x^T Dy + 2x^T Dy$$
(3)

$$(||x|| + ||y||)^2 = (\sqrt{x^T Dx})^2 + (\sqrt{y^T Dy})^2 = x^T Dx + y^T Dy + 2\sqrt{x^T Dx}\sqrt{y^T Dy}$$
(4)

Now we show that $x^T Dy \leq \sqrt{x^T Dx} \sqrt{y^T Dy}$, which is equivalent to

$$\left(\sum_{i=0}^{m-1} \delta_i x_i y_i\right)^2 \le \left(\sum_{i=0}^{m-1} \delta_i x_i^2\right) \left(\sum_{i=0}^{m-1} \delta_i y_i^2\right) \tag{5}$$

$$\iff \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} \delta_i \delta_j x_i y_i x_j y_j \le \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} \delta_i \delta_j x_i^2 y_j^2$$

$$(6)$$

$$\iff \sum_{i=0}^{m-1} \sum_{j=0}^{i-1} \delta_i \delta_j (2x_i y_i x_j y_j) + \sum_{i=0}^{m-1} \delta_i^2 x_i y_i x_i y_i \le \sum_{i=0}^{m-1} \sum_{j=0}^{i-1} \delta_i \delta_j (x_i^2 y_j^2 + x_j^2 y_i^2) + \sum_{i=0}^{m-1} \delta_i^2 x_i^2 y_i^2$$
 (7)

$$\iff \sum_{i=0}^{m-1} \sum_{j=0}^{i-1} \delta_i \delta_j (2x_i y_i x_j y_j) \le \sum_{i=0}^{m-1} \sum_{j=0}^{i-1} \delta_i \delta_j (x_i^2 y_j^2 + x_j^2 y_i^2)$$
 (8)

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which obivously holds if we apply basic inequality on each (i, j) pair,

$$2x_i y_i x_j y_j = 2(x_i y_j)(x_j y_i) \le x_i^2 y_j^2 + x_j^2 y_i^2$$
(9)

Since we have proved $x^T Dy \leq \sqrt{x^T Dx} \sqrt{y^T Dy}$, then

$$||x+y||^2 \le (||x|| + ||y||)^2 \tag{10}$$

which leads to desired triangle inequality since $||\cdot|| \ge 0$,

$$||x+y|| \le ||x|| + ||y|| \tag{11}$$

Since all three property have been proved, it can be concluded that

$$||\cdot||$$
 defined by $||x|| = \sqrt{x^T Dx}$ is a norm. (12)

(b) Show that $||\cdot||$ is a matrix norm.

To prove $||\cdot||$ is a matrix norm, we have to show all the following three property holds:

- If $A \neq 0$, then ||A|| > 0.
- For arbitrary scalar α and matrix A, $||\alpha A|| = |\alpha| \cdot ||A||$.
- For arbitrary matrix A and B, $||A + B|| \le ||A|| + ||B||$.

Now we turn to prove each of them individually.

Proof. Since D is diagonal with positive diagonal elements, then $\forall i, \ \delta_i > 0$ holds. And Since $A \neq 0$, then there is at least one column vector that is not zero vector. Let us assume it is the j-th column, a_j , that is non-zero. Then

$$||A|| = ||DA||_2 = \max_{||x||_2 \neq 0} \frac{||DAx||_2}{||x||_2} \ge \frac{||DAe_j||_2}{||e_j||_2} > 0$$
(13)

Therefore, we proved that if $A \neq 0$, then ||A|| > 0.

Proof. According to the class notes, $||\cdot||_2$ is a norm (since it is one of p-induced-norm) and then for arbitrary scalar β and arbitrary matrix B,

$$||\alpha B||_2 = |\beta| \cdot ||B||_2 \tag{14}$$

Now we consider $||\alpha A||$

$$||\alpha A|| = ||D(\alpha A)||_2 \tag{15}$$

$$= ||\alpha DA||_2 \tag{16}$$

$$= |\alpha| \cdot ||DA||_2 \qquad \text{natural consequence of (19)}$$

$$= |\alpha| \cdot ||A|| \tag{18}$$

Thus, we proved that $||\alpha A|| = |\alpha| \cdot ||A||$.

Proof. According to the class notes, $||\cdot||_2$ is a norm (since it is one of *p*-induced-norm) and then for arbitrary matrix C and arbitrary matrix D,

$$||C+D||_2 \le ||C||_2 + ||D||_2 \tag{19}$$

Now we consider ||A + B|| for arbitrary matrix A and B,

$$||A + B|| = ||D(A + B)||_2 \tag{20}$$

$$= \max_{x \neq 0} \frac{||DAx + DBx||_2}{||x||_2} \tag{21}$$

$$\leq \max_{x \neq 0} \frac{||DAx||_2 + ||DBx||_2}{||x||_2} \tag{22}$$

$$= \max_{x \neq 0} \left(\frac{||DAx||_2}{||x||_2} + \frac{||DBx||_2}{||x||_2} \right) \tag{23}$$

$$\leq \max_{x \neq 0} \frac{||DAx||_2}{||x||_2} + \max_{y \neq 0} \frac{||DBy||_2}{||y||_2} \tag{24}$$

$$= ||DA||_2 + ||DB||_2 = ||A|| + ||B|| \tag{25}$$

Hence, we proved that $||A + B|| \le ||A|| + ||B||$.

Since all three property have been proved, it can be concluded that

$$||\cdot||$$
 defined by $||A|| = ||DA||_2$ is a norm. (26)

Exercise 2.

(a) Show that $(..)^{-1} = (..)$.

Proof.

$$\left(\begin{array}{c|c|c} L_{00} & 0 \\ \hline l_{10}^T & \lambda_{11} \end{array}\right) \left(\begin{array}{c|c|c} L_{00}^{-1} & 0 \\ \hline -\frac{l_{10}^T L_{00}^{-1}}{\lambda_{11}} & \frac{1}{\lambda_{11}} \end{array}\right) = \left(\begin{array}{c|c|c} L_{00} L_{00}^{-1} & 0 \\ \hline l_{10}^T L_{00}^{-1} & \frac{l_{10}^T L_{00}^{-1}}{\lambda_{11}} \cdot \lambda_{11} & \frac{1}{\lambda_{11}} \cdot \lambda_{11} \end{array}\right) = \left(\begin{array}{c|c|c} I & 0 \\ \hline 0 & 1 \end{array}\right) = I \quad (27)$$

Multiply both side on the left with $\left(\begin{array}{c|c} L_{00} & 0 \\ \hline l_{10}^T & \lambda_{11} \end{array}\right)^{-1}$ and then we have (assume all inversion exists)

$$\left(\begin{array}{c|c}
L_{00} & 0 \\
\hline
l_{10}^T & \lambda_{11}
\end{array}\right)^{-1} = \left(\begin{array}{c|c}
L_{00}^{-1} & 0 \\
\hline
-\frac{l_{10}^T L_{00}^{-1}}{\lambda_{11}} & \frac{1}{\lambda_{11}}
\end{array}\right)$$
(28)

(b) Show that $H_1H_0 = ...$

According to given formula for H_i , we have

$$H_0 = I - \frac{1}{\tau_0} u_0 u_0^T \text{ and } H_1 = I - \frac{1}{\tau_1} u_1 u_1^T$$
 (29)

Now we manipulate H_1H_0 ,

$$H_1 H_0 = \left(I - \frac{1}{\tau_1} u_1 u_1^T\right) \left(I - \frac{1}{\tau_0} u_0 u_0^T\right) \tag{30}$$

$$= I - \frac{1}{\tau_1} u_1 u_1^T - \frac{1}{\tau_0} u_0 u_0^T + \frac{1}{\tau_0 \tau_1} u_1 u_1^T u_0 u_0^T$$
(31)

$$= I - (u_0|u_1) \left(\frac{\frac{1}{\tau_0} | 0}{-\frac{u_0^T u_1}{\tau_0 \tau_1} | \frac{1}{\tau_1}} \right) (u_0|u_1)^T$$
(32)

$$= I - (u_0|u_1) \left(\frac{\tau_0 | 0}{u_0^T u_1 | \tau_1} \right)^{-1} (u_0|u_1)^T$$
(33)

where $\tau_0 = \frac{u_0^T u_0}{2}$ and $\tau_1 = \frac{u_1^T u_1}{2}$. Hence, it is concluded that (assume all inversion exists)

$$H_1 H_0 = I - (u_0 | u_1) \left(\frac{\tau_0 | 0}{u_0^T u_1 | \tau_1} \right)^{-1} (u_0 | u_1)^T$$
(34)

(c) Show that $(I - \frac{1}{\tau_1}u_1u_1^T)(I - U_0L_{00}^TU_0^T) = I - ...$

$$(I - \frac{1}{\tau_1} u_1 u_1^T)(I - U_0 L_{00}^T U_0^T) = I - \frac{1}{\tau_1} u_1 u_1^T - U_0 L_{00}^T U_0^T + \frac{1}{\tau_1} u_1 u_1^T U_0 L_{00}^T U_0^T$$
(35)

$$= I - (U_0|u_1) \left(\frac{L_{00}^{-1} | 0}{-u_1^T U_0 L_{00}^{-1} / \tau_1 | \frac{1}{\tau_1}} \right) (U_0|u_1)^T$$
 (36)

$$= I - (U_0|u_1) \left(\frac{L_{00} \mid 0}{u_1^T U_0 \mid \tau_1}\right)^{-1} (U_0|u_1)^T$$
(37)

where $\tau_1 = \frac{u_1^T u_1}{2}$. Thus, it is concluded that (assume all inversion exists)

$$(I - \frac{1}{\tau_1} u_1 u_1^T)(I - U_0 L_{00}^T U_0^T) = I - (U_0 | u_1) \left(\frac{L_{00} | 0}{u_1^T U_0 | \tau_1} \right)^{-1} (U_0 | u_1)^T$$
(38)

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(d) Show that $H_{k-1} \cdots H_1 H_0 = I - U L^{-1} U^H$

We can do mathematical induction on m. We separate the discussion of k = 1 and k > 1.

• Particular Case: k = 1,

Proof.

$$H_0 = I - \frac{1}{\tau_0} u_0 u_0^T = I - \underbrace{(u_0)}_{U_{(0)}} \underbrace{(\frac{1}{\tau_0})}_{L_{(0)}^{-1}} \underbrace{(u_0)^T}_{U_{(0)}^T}$$
(39)

Hence,
$$H_{k-1} \cdots H_1 H_0 = I - U L^{-1} U^H$$
 holds for $k = 1$.

Note that this case is particular because it derives matrix which is indeed scalar.

- Base Case: k = 2, this can be proved by using result of (b).
- Inductive Case: assume that for $p \geq 2$, (I.H.)

$$H_{p-1} \cdots H_1 H_0 = I - U_{(p-1)} L_{(p-1)}^{-1} U_{(p-1)}^H$$
 (40)

show that there exist one lower triangular matrix $L_{(p)}$ and one matrix $U_{(p)}$, such that

$$H_p H_{p-1} \cdots H_1 H_0 = I - U_{(p)} L_{(p)}^{-1} U_{(p)}^H$$
 (41)

holds.

Proof. With application of the result of (c), we have

$$H_p(H_{p-1}H_{p-2}\cdots H_1H_0) = \left(1 - \frac{1}{\tau_p}u_p u_p^T\right)\left(I - U_{(p-1)}L_{(p-1)}^{-1}U_{(p-1)}^H\right)$$
(42)

$$= I - \underbrace{(U_{(p-1)}|u_p)}_{U_{(p)}} \underbrace{\left(\begin{array}{c|c} L_{(p-1)} & 0 \\ \hline u_p^T U_{(p-1)} & \tau_p \end{array}\right)^{-1}}_{L_{(p)}^{-1}} \underbrace{(U_{(p-1)}|u_p)^T}_{U_{(p)}^T}$$
(43)

$$=I-U_{(p)}L_{(p)}^{-1}U_{(p)}^{T}$$
(44)

where
$$U_{(p)} = (U_{(p-1)}|u_p), L_{(p)} = \left(\begin{array}{c|c} L_{(p-1)} & 0 \\ \hline u_p^T U_{(p-1)} & \tau_p \end{array}\right)$$
 and $\tau_p = \frac{u_p^T u_p}{2}$.

• By the principle of mathematical induction, it can be concluded that

$$H_{k-1} \cdots H_1 H_0 = I - U L^{-1} U^H \tag{45}$$

holds for all k > 0.

Exercise 3.

(a) Relationship between m, n and r.

$$rank(A) = r \le \min(m, n) \tag{46}$$

- (b) Reduced SVD in terms of U, V and Σ .
 - $A = U_r \Sigma_r V_r^T$, where $U_r = U_L$, $\Sigma_r = \Sigma_{TL}$ and $V_r = V_L$.

$$A = U\Sigma V^T = (U_L|U_R) \left(\frac{\Sigma_{TL} \mid 0}{0 \mid 0}\right) (V_L|V_R)^T = U_L \Sigma_{TL} V_L^T$$
(47)

• $(A^T A)^{-1} = U_r \Sigma_r V_r^T$, where $U_r = V_L^{-T}$, $\Sigma_r = \Sigma_{TL}^{-1} \Sigma_{TL}^{-1}$ and $V_r = V_L^{-T}$.

$$(A^{T}A)^{-1} = ((U\Sigma V^{T})^{T}U\Sigma V^{T})^{-1}$$
(48)

$$= \left(V \Sigma^T U^T U \Sigma V^T\right)^{-1} \tag{49}$$

$$= \left(V \Sigma \Sigma V^T\right)^{-1} \tag{50}$$

$$= \left((V_L | V_R) \left(\begin{array}{c|c} \Sigma_{TL} & 0 \\ \hline 0 & 0 \end{array} \right) \left(\begin{array}{c|c} \Sigma_{TL} & 0 \\ \hline 0 & 0 \end{array} \right) (V_L | V_R)^T \right)^{-1}$$
 (51)

$$= \left(V_L \Sigma_{TL} \Sigma_{TL} V_L^T\right)^{-1} \tag{52}$$

$$= V_L^{-T} \Sigma_{TL}^{-1} \Sigma_{TL}^{-1} V_L^{-1} \tag{53}$$

$$= V_L^{-T} \Sigma_{TL}^{-1} \Sigma_{TL}^{-1} (V_L^{-T})^T \tag{54}$$

• $(A^TA)^{-1}A^T = U_r\Sigma_rV_r^T$, where $U_r = V_L^{-T}$, $\Sigma_r = \Sigma_{TL}^{-1}$ and $V_r = U_L$.

$$(A^{T}A)^{-1}A^{T} = V_{L}^{-T}\Sigma_{TL}^{-1}\Sigma_{TL}^{-1}V_{L}^{-1}V_{L}\Sigma_{TL}^{T}U_{L}^{T}$$

$$(55)$$

$$=V_L^{-T}\Sigma_{TL}^{-1}\Sigma_{TL}^{-1}\Sigma_{TL}^TU_L^T \tag{56}$$

$$=V_L^{-T}\Sigma_{TL}^{-1}U_L^T\tag{57}$$

• $A(A^TA)^{-1} = U_r \Sigma_r V_r^T$, where $U_r = U_L$, $\Sigma_r = \Sigma_{TL}^{-1} \Sigma_{TL}^{-1}$ and $V_r = V_L^{-T}$.

$$A(A^{T}A)^{-1} = U_{L}\Sigma_{TL}V_{L}^{T}V_{L}^{-T}\Sigma_{TL}^{-1}\Sigma_{TL}^{-1}V_{L}^{-1}$$
(58)

$$=U_L \Sigma_{TL} \Sigma_{TL}^{-1} \Sigma_{TL}^{-1} V_L^{-1} \tag{59}$$

$$=U_L \Sigma_{TL}^{-1} V_L^{-1} \tag{60}$$

$$= U_L \Sigma_{TL}^{-1} (V_L^{-T})^T \tag{61}$$

• $A(A^TA)^{-1}A^T = U_r\Sigma_rV_r^T$, where $U_r = U_L$, $\Sigma_r = I^{r\times r}$ and $V_r = U_L$.

$$A(A^{T}A)^{-1}A^{T} = (U_{L}\Sigma_{TL}^{-1}V_{L}^{-1})V_{L}\Sigma_{TL}^{T}U_{L}^{T}$$
(62)

$$= U_L \Sigma_{TL}^{-1} \Sigma_{TL}^T U_L^T \tag{63}$$

$$=U_L I U_L^T (64)$$

Exercise 4.

(a) $\psi_1 = (v_{11} - \delta v_{11}) \check{\chi}_1$ where δv_{11} is small.

Proof.

$$\psi_1 = [v_{11}\check{\chi}_1]_* = \frac{v_{11}\check{\chi}_1}{1 + \epsilon_*} = (1 - \frac{\epsilon_*}{1 + \epsilon_*})v_{11}\check{\chi}_1 = (v_{11} - \frac{\epsilon_*v_{11}}{1 + \epsilon_*})\check{\chi}_1 \equiv (v_{11} + \delta v_{11})\check{\chi}_1 \tag{65}$$

where

$$\delta v_{11} = -\frac{\epsilon_* v_{11}}{1 + \epsilon_*}, \text{ where } |\epsilon_*| \le \mathbf{u}$$
 (66)

Then

$$|\delta v_{11}| = |-\frac{\epsilon_*}{1 + \epsilon_*} v_{11}| \tag{67}$$

$$=\frac{|\epsilon_*|}{|1+\epsilon_*|}|v_{11}|\tag{68}$$

$$\leq \frac{\mathbf{u}}{|1 + \epsilon_*|} |v_{11}| \tag{69}$$

$$\leq \frac{\mathbf{u}}{1 + |\epsilon_*|} |v_{11}| \tag{70}$$

$$\leq \frac{\mathbf{u}}{1 + |\epsilon_*| - |\epsilon_*| - \mathbf{u}} |v_{11}| \tag{71}$$

$$= \frac{\mathbf{u}}{1 - \mathbf{u}} |v_{11}| = \gamma_1 |v_{11}| \tag{72}$$

Hence, we proved that

$$\psi_1 = (v_{11} - \delta v_{11})\check{\chi}_1 \text{ where } |\delta v_{11}| = \gamma_1 |v_{11}|$$
 (73)

(b)

Proof. Start from dot product. We directly use the corollary in notes.

$$d \stackrel{\Delta}{=} [u_{12}^T \check{x_2}] = (u_{12}^T + \delta u_{12}^T) \check{x_2} , \text{ where } |\delta u_{12}^T| \le \gamma_k |u_{12}^T| \le \gamma_{k+1} |u_{12}^T|$$
 (74)

Then we consider the subtraction step with Standard Computational Model (SCM).

$$s \stackrel{\Delta}{=} [\psi_1 - d] = (\psi_1 - d)(1 + \epsilon_-) = (\psi_1 - d) + (\psi_1 - d)\epsilon_- \equiv (\psi_1 - d) + \delta\psi_1 = (\psi_1 + \delta\psi_1) - d$$
 (75)

where $|\delta\psi_1| = |(\psi_1 - d)\epsilon_-| \le |\psi_1\epsilon_-| = |\epsilon_-||\psi_1| \le \mathbf{u}|\psi_1|$. Then we consider the division step with Alternative Computational Model (ACM).

$$\tilde{\chi}_1 = \left[\frac{s}{v_{11}}\right] = \frac{s}{v_{11}} (1 + \epsilon_f)^{-1} = \frac{s}{v_{11} (1 + \epsilon_f)}$$
(76)

which can be rewritten as

$$(v_{11} + \delta v_{11})\check{\chi}_1 = s \tag{77}$$

where $|\delta v_{11}| = |\epsilon_{/}v_{11}| \leq |\epsilon_{/}| \cdot |v_{11}| \leq \mathbf{u}|v_{11}|$. Then we have

$$(v_{11} + \delta v_{11})\check{\chi}_1 = (\psi_1 + \delta \psi_1) - d = (\psi_1 + \delta \psi_1) - (u_{12}^T + \delta u_{12}^T)\check{x}_2$$
(78)

where

$$|\delta v_{11}| \le \mathbf{u}|v_{11}|, \ |\delta \psi_1| \le \mathbf{u}|\psi_1|, \ |\delta u_{12}^T| \le \gamma_{k+1}|u_{12}^T|$$
 (79)

(c) Induction for the desired result

To prove the desired result, let us do mathematical induction on k (the iteration of algorithm).

• Base Case: k = 0

Proof. In this case, $U^{0\times 0}$ does not participate in computation, v_{11} is the right-bottom-most element, and no pre-computed \check{x}_2 . Hence, it is natural that

$$(v_{11} + \delta v_{11})\dot{\chi}_1 = (\psi_1 + \delta \psi_1) \tag{80}$$

which indicates that $(U + \Delta U)\check{x} = (y + \delta y)$ holds for k = 0. (first iteration)

• Inductive case: Assume that at p-th iteration (p > 0), pre-computed $\check{x}_{2(p)}$ satisfy

$$(U_{(p)} + \Delta U_{(p)}) \check{x}_{2(p)} = (y_{2(p)} + \Delta y_{2(p)}) \tag{81}$$

where $|\Delta U_{(p)}| \leq \gamma_n |U_{(p)}|$ and $|\delta y_{2(p)}| \leq \mathbf{u} |y_{2(p)}|$, (I.H.) holds.

Show that for the pre-computed \check{x}_2 at next iteration $\check{x}_{2(p+1)} = \left(\frac{\check{\chi}_{1(p)}}{\check{x}_{2(p)}}\right)$ and $y_{2(p+1)} = \left(\frac{\psi_{1(p)}}{y_{2(p)}}\right)$

$$(U_{(p+1)} + \Delta U_{(p+1)}) \check{x}_{2(p+1)} = (y_{(p+1)} + \Delta y_{(p+1)})$$
(82)

where $|\Delta U_{(p+1)}| \leq \gamma_n |U_{(p+1)}|$ and $|\delta y_{2(p+1)}| \leq \mathbf{u}|y_{2(p+1)}|$, holds for some upper triangle $U_{(p+1)}$.

Proof. In terms of result of (b), we have

$$(v_{11(p)} + \delta v_{11(p)}) \check{\chi}_{1(p)} + (u_{12(p)}^T + \delta u_{12(p)}^T) \check{x}_{2(p)} = (\psi_{1(p)} + \delta \psi_{1(p)})$$
(83)

where $\delta v_{11(p)} \leq \mathbf{u}|v_{11(p)}|$, $\delta \psi_{1(p)} \leq \mathbf{u}|\psi_{1(p)}|$, and $\delta u_{12(p)}^T \leq \gamma_{p+1}|u_{12(p)}^T|$. Combined with (I.H.)

$$(U_{(p)} + \Delta U_{(p)}) \check{x}_{2(p)} = (y_{2(p)} + \Delta y_{2(p)})$$
(84)

we have

$$\left(\begin{array}{c|c} v_{11(p)} + \delta v_{11(p)} & u_{12(p)}^T + \delta u_{12(p)}^T \\ \hline 0 & U_{(p)} + \Delta U_{(p)} \end{array}\right) \left(\begin{array}{c} \check{\chi}_{1(p)} \\ \check{x}_{2(p)} \end{array}\right) = \left(\begin{array}{c} \psi_{1(p)} + \delta \psi_{1(p)} \\ \hline y_{2(p)} + \Delta y_{2(p)} \end{array}\right)$$
(85)

where $|\Delta U_{(p)}| \leq \gamma_n |U_{(p)}|$, $|\delta v_{11(p)}| \leq \mathbf{u}|v_{11(p)}| \leq \gamma_n |v_{11(p)}|$, $|\delta u_{12(p)}^T| \leq \gamma_{p+1} |u_{12(p)}^T| \leq \gamma_n |u_{12(p)}^T|$ and $\delta \psi_{1(p)} \leq \mathbf{u}|\psi_{1(p)}|$, $|\delta y_{2(p)}| \leq \mathbf{u}|y_{2(p)}|$. (Note that $0 \leq p \leq n-1$) which is equivalent to

$$\left(\underbrace{\left(\begin{array}{c|c} v_{11(p)} & u_{12(p)}^T \\ \hline 0 & U_{(p)} \end{array}\right)}_{U_{(p+1)}} + \underbrace{\left(\begin{array}{c|c} \delta v_{11(p)} & \delta u_{12(p)}^T \\ \hline 0 & \Delta U_{(p)} \end{array}\right)}_{\Delta U_{(p+1)}} \underbrace{\left(\begin{array}{c|c} \check{\chi}_{1(p)} \\ \check{x}_{2(p)} \end{array}\right)}_{\check{x}_{2(p+1)}} = \underbrace{\left(\begin{array}{c|c} \psi_{1(p)} \\ \hline y_{2(p)} \end{array}\right)}_{y_{2(p+1)}} + \underbrace{\left(\begin{array}{c|c} \delta \psi_{1(p)} \\ \hline \Delta y_{2(p)} \end{array}\right)}_{\delta y_{2(p+1)}} \right) (86)$$

$$\left(U_{(p+1)} + \Delta U_{(p+1)}\right) \check{x}_{2(p+1)} = \left(y_{2(p+1)} + \delta y_{2(p+1)}\right) (87)$$

where
$$|\Delta U_{(p+1)}| \leq \gamma_n |U_{(p+1)}|$$
 and $|\delta y_{2(p+1)}| \leq \mathbf{u} |y_{2(p+1)}|$.
Hence, we successfully proved (82).

• By principle of mathematical induction, it is proved w.l.o.g. that

$$(U + \Delta U)\check{x} = (y + \delta y)$$
, where $|\Delta U| \le \gamma_n |U|$ and $|\delta y| \le \mathbf{u}|y|$ (88)