

## LECTURE 28

I. Rigid Transformations

II. "Active" vs. "Passive" view point.

III. Orthogonal Projections

IV. Least Squares Problem

[V. Least Squares Approximation]

Read 4.6 in JR&A 3<sup>rd</sup> Ed.

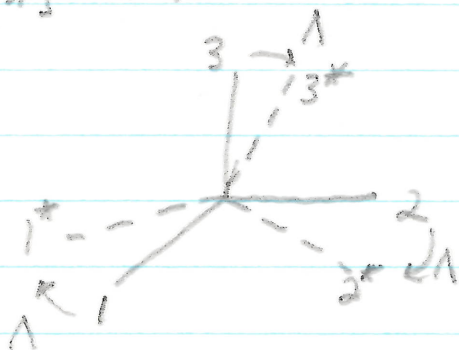
3.1-3.4 in G. Strang 3<sup>rd</sup> Ed.

# I. RIGID TRANSFORMATIONS

28.1F

Definition 28.1: A rigid transformation  $\Lambda: V \rightarrow V$  is one which transforms an o.n. basis into an o.n. basis.

$\{e_1, \dots, e_n\} = \text{old o.n. basis} \xrightarrow{\Lambda} \{e_1^*, \dots, e_n^*\} = \text{new o.n. basis}$



Proposition 28.1: A rigid transformation is orthogonal.

Let  $\Lambda: 1. e_i^* = \Lambda(e_i) = e_j \Lambda_{ji}$

2. The matrix elements  $\Lambda_{ji}$  are computed using the orthonormality

$$e_k \cdot e_i^* = e_k \cdot e_j \Lambda_{ji} = \Lambda_{ki}$$

3. Thus

$$\delta_{ki} = e_k^* \cdot e_i^* = e_k \Lambda_{kl} \cdot e_j \Lambda_{ji}$$

$$\begin{matrix} \Lambda_{11} & \Lambda_{12} \\ \vdots & \vdots \\ \Lambda_{n1} & \Lambda_{n2} \end{matrix} = \begin{matrix} \Lambda_{k1} & \Lambda_{k2} \\ \vdots & \vdots \\ \Lambda_{kn} & \Lambda_{kn} \end{matrix} \left. \begin{matrix} \text{"} \ell^{\text{th}} \text{ column} \times i^{\text{th}} \text{ col."} \\ \text{"index notation"} \end{matrix} \right\} \delta_{ki} = (\Lambda^T \Lambda)_{ki}$$

$$\boxed{I = \Lambda^T \Lambda}$$

"matrix notation"

Comment: The matrix element  $\Lambda_{ki}$  can be computed using orthonormality

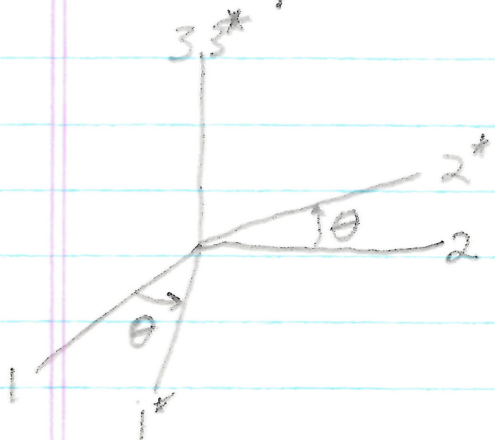
28.2

$$e_k \cdot e_i^* = e_k \cdot e_j \Lambda_{ji}^* = \Lambda_{ki} = \cos(e_k, e_i^*)$$



= cos of  $\angle$  between old k-axis and new i-axis.

Example 1: Rotation by  $\theta$  around z-axis



$$[\Lambda_{ki}] = [e_k \cdot e_i^*]$$

$$= \begin{bmatrix} \cos \theta & \cos(\frac{\pi}{2} + \theta) & \cos \frac{\pi}{2} \\ \cos(\frac{\pi}{2} - \theta) & \cos \theta & \cos \frac{\pi}{2} \\ \cos \frac{\pi}{2} & \cos \frac{\pi}{2} & \cos 0 \end{bmatrix}$$

$$= \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

1.) Rotate the vector using  $\Lambda$ :

$$x \mapsto x^* = \Lambda(x)$$

$$\vec{e}_i x^i \mapsto \Lambda(\vec{e}_i x^i) = \Lambda(\vec{e}_i) x^i \quad \text{[SKIP THIS]}$$

$$= \vec{e}_i^* x^i \quad \text{where } \vec{e}_i^* = \vec{e}_j \Lambda_{ji}^*$$

$$= \text{rotated vector (different from } x)$$

2.) change basis but vector stays fixed:

$$\text{Let } \vec{e}_i x^i = \vec{x} = \vec{e}_k^* x^{*k} \quad \text{same vector}$$

but

$$\text{or } \vec{e}_j x^j = \vec{e}_j \Lambda_{jk}^* x^{*k}$$

$$x^j = \Lambda_{jk}^* x^{*k}$$

$$[x]_{\text{old}} = \Lambda [x]_{\text{new}}$$

different rep'n.

active view point

passive view point

## II. ACTIVE vs PASSIVE VIEWPOINT.

28.3

A rotation  $\Lambda$  can be used for two different purposes:

1. Rotate a vector using  $\Lambda$ :

$$\vec{x} \mapsto \vec{x}^* = \Lambda(\vec{x})$$

$$\begin{aligned} \vec{e}_i x^i \mapsto \Lambda(\vec{e}_i x^i) &= \Lambda(\vec{e}_i) x^i \\ &= (\vec{e}_j \Lambda_{ji}) x^i \\ &= \vec{e}_j (\Lambda_{ji} x^i) \end{aligned}$$

same basis

$$\vec{x}^* = \vec{e}_j x^{*j} = \text{rotated vector}$$

Thus we have a different vector

but the basis is the same,

i.e. the orientation of the basis vectors remains fixed relative to the fixed stars while the vector rotates

In physics and engineering this use of  $\Lambda$

is called the active viewpoint,

2. change the basis, but keep the vector fixed (relative to the fixed stars):

$$\vec{e}_i \cdot x^i = \vec{x} = e_R^+ x^{*k} \quad (\text{same vector different basis})$$

$$\vec{e}_i \cdot x^i = \vec{e}_i \cdot \Lambda_{ik} x^{*k}$$

Thus

$$x^i = \Lambda_{ik} x^{*k} \quad x^{*i} = P_{ik} x^k \quad \Lambda_{ik}^{-1} (= \Lambda_{ki})$$

This expresses a transition between two representations whose transition matrix (see page 19.5)

is

$$P_{ik} = \Lambda_{ki}^{-1}$$

(Indeed, using  $\Lambda_{ki}^{-1} \Lambda_{ik} = \delta_{ij}$ , one obtains

$$x^{*i} = \Lambda_{ki}^{-1} x^k, \text{ the transition from the old}$$

$[x^i]$  to the new  $[x^{*i}]$  representation of  $\vec{x}$ .)

Using  $\Lambda$  for this purpose is called the passive

viewpoint. Thus one has

the active viewpoint, where one rotates the vector  $\vec{x}$  while keeping the

basis fixed (relative to the fixed stars) vs  
the passive viewpoint where one  
keeps the vector fixed (relative to the  
fixed stars) while changing the reference  
frame by means of a rotation.

### III. Orthogonal Projections

28.6

The Gram-Schmidt process consisted of removing the orthogonal projections

$$\frac{\langle u_j | v \rangle}{\|u_j\|^2} \quad j=1, \dots, N$$

from  $v$ ,

$$h^* \equiv v - \underbrace{\left[ \frac{u_1 \langle u_1 | v \rangle}{\|u_1\|^2} + \dots + \frac{u_N \langle u_N | v \rangle}{\|u_N\|^2} \right]}_{w^*}$$

Here  $[\dots] \equiv w^*$  is the orthogonal projection of  $v$  onto the subspace  $S_p(\{u_j\}_{j=1}^N) = W_N$

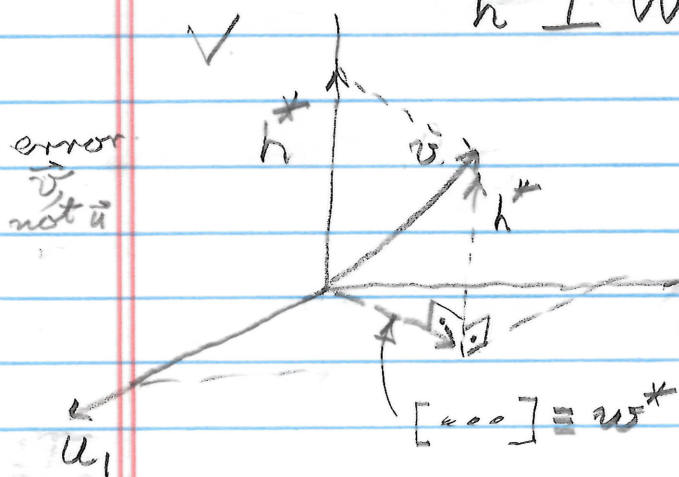
Removing these projections resulted in  $h^*$ , a vector which was orthogonal to  $W_N$

$$h^* \perp W : \langle u_j | h^* \rangle = 0; \quad j=1, \dots, N,$$

whenever the vectors

$$u_1, \dots, u_N$$

where mutually orthogonal.

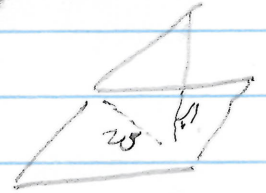


## IV, LEAST SQUARES PROBLEM 28.7

One of the consequences of this orthogonality the observation is that  $h^*$  minimizes the squared distance of  $v$  from  $W_N$ . In other words,

$\exists$  an optimal  $w^* \in W_N$  such that

$$\|h^*\|^2 \leq \|v - w\|^2 \quad \forall w \in W_N.$$



This observation motivates

the following orthogonal projection problem:

### Least-Squares Problem

Let  $V$  be an inner product space

Let  $W_N \subset V$  be a subspace.

GIVEN  $v \in V$ , FIND in  $W_N$  a vector

$w^*$  such that

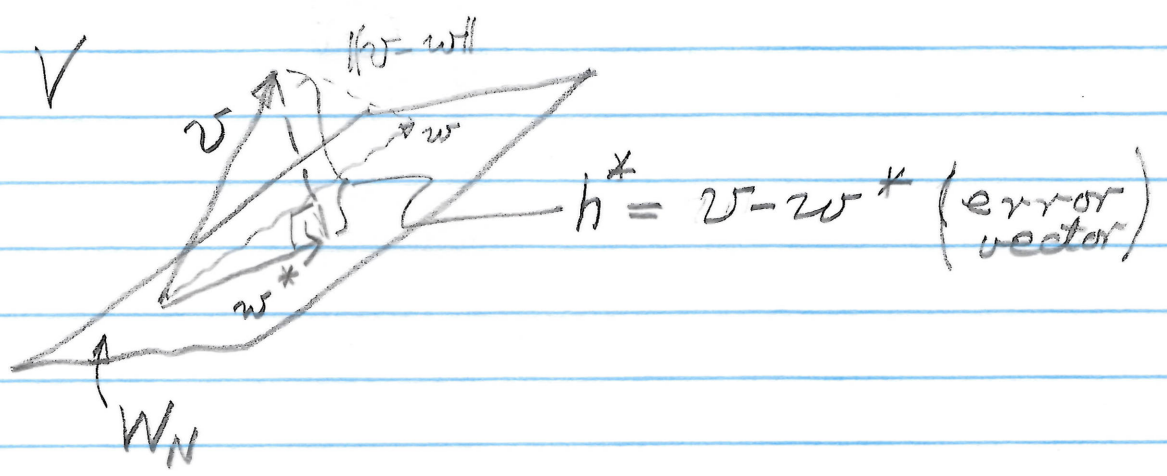
$$\|v - w^*\| = \min_{w \in W_N} \|v - w\|$$



i.e.

$$\|v - w^*\| \leq \|v - w\|$$

$$\forall w \in W_N$$



Comment:

- (i) the orthogonal projection of  $v$  onto  $W_N$  or
- (ii) nearest vector in  $W_N$  to  $v$
- (iii) the least squares approximation to  $v$ .