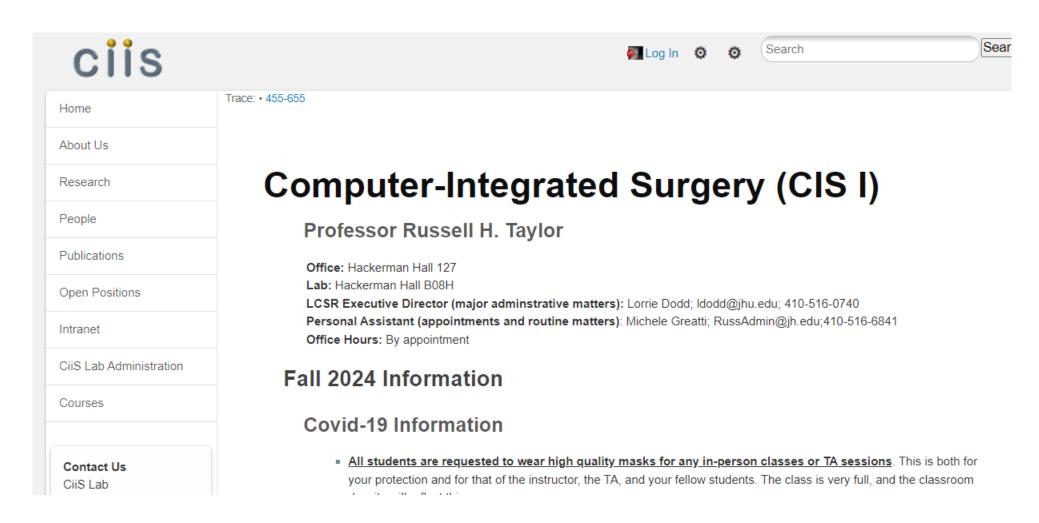
#### Course Wiki: <a href="https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655">https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655</a>



#### Course Wiki: <a href="https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655">https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655</a>

#### Section and TA office hour times and location

#### Tatiana Kashtanova

- Email: tkashta1@jhu.edu
- Office Hours (starting September 9)
  - Time: Monday, 10 am 11 am
  - Location: Zoom
  - Mttps://JHUBlueJays.zoom.us/j/99052831625?pwd=AFMJsShozAjWfMKpYv47JqLqjz3hAN.1
  - Meeting ID: 990 5283 1625
  - Passcode: 096011
- Discussion sections will be announced on Piazza

#### Meetings with a TA (subject to change):

- 9-Sep: Math
- 16-Sep: HW1
- 23-Sep: HW2
- 30-Sep: PA general, PA1
- TBD: PA Intro
- 7-Oct: HW1 Review
- 14-Oct: PA2
- 21-Oct: PA3
- 28-Oct: HW3
- 4-Nov: HW2 Review
- 11-Nov: HW4, PA4
- 18-Nov: HW3 Review
- 25-Nov: N/A (Thanksgiving)
- 2-Dec: PA5

I will upload my slides here

Course Wiki: <a href="https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655">https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:455-655</a>

#### **Organizational Information**

Fall 2024 Schedule

Schedule: https://ciis.lcsr.jhu.edu/doku.php?id=courses:455-655:2024:fall-2024-schedule

# CIS I (601.455/655) Fall 2024 Schedule

Note: This page is subject to change

- Lecture slides
- Supplementary material
- Assignments (hand-out & due dates)

### Piazza: https://piazza.com/jhu/fall2024/601455655

- Course announcements
- Find a partner
- Q&A
- Typos / errors
- Private message to the professor & TA

#### **Partner:**

- Can be changed between assignments
- Do not abandon anybody before the due date!



#### **Special circumstances / Accommodations:**

- Sport / science competitions
- Conferences
- Marriage
- Scheduled health-related procedures
- Etc. expected
- Sickness
- Fire
- Etc. unexpected
- Disability

→ Do not come to the class. Tell us!

Contact "Student Disability Services"! They will contact us.

Tell us in advance!

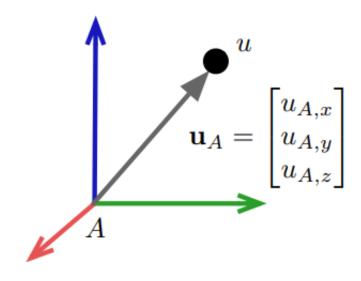
Review – Russell H. Taylor (2024). Fall 2024 Organization Lecture – for details

# **CIS Math Tutorial**

#### References:

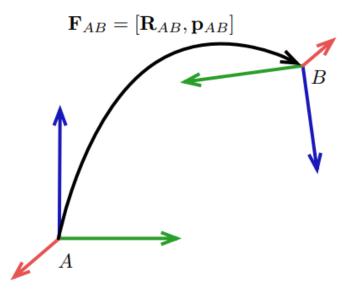
Benjamin D. Killeen (2022). Frame Transformations in Computer Integrated Surgery: A Graphical Introduction

Russell H. Taylor (2024). 600.455/655 Lecture Notes: Basic Mathematical Methods for CIS



A point  $oldsymbol{u}$  as measured in frame  $oldsymbol{A}$ 

- A **frame** is a basis for numerical measurements of object locations, orientations, or poses
- A point is a singular location in space
- Vector  $u_A$  defines the position of u relative to frame A

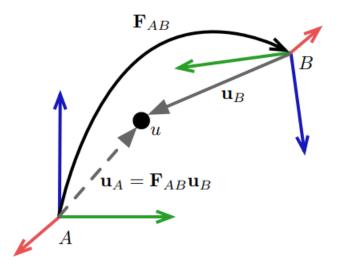


#### Frame transformation "A from B"

$$\boldsymbol{F}_{AB} = [\boldsymbol{R}_{AB}, \boldsymbol{p}_{AB}]$$

A measurement of frame **B** pose (rotation

+ translation) with respect to frame A



$$u_A = F_{AB} u_B = [R_{AB}, p_{AB}]u_B = R_{AB} u_B + p_{AB}$$

- $u_B$  is the measurement of u in frame B
- $F_{AB}$  known

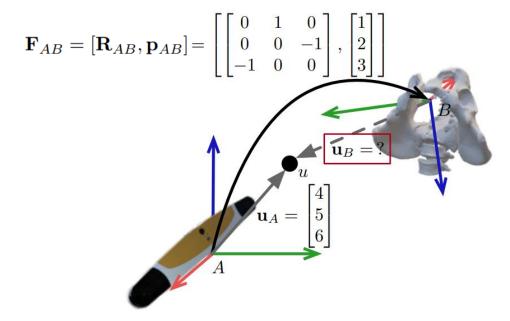
The right-hand subscript of the transform should match the subscript of the point  $\mathbf{F}_{AB}\mathbf{F}_{BC}=\mathbf{F}_{AC}$ 

#### **Inverse Transformations**

$$F_{AB}^{-1} = [R_{AB}^{-1}, -R_{AB}^{-1} p_{AB}]$$
 $F_{AB}^{-1} = F_{BA}$ 

Rotation matrices are orthonormal:

$$R^{-1} = R^T$$



$$\mathbf{u}_{B} = \mathbf{F}_{BA} \mathbf{u}_{A} = \mathbf{F}_{AB}^{-1} \mathbf{u}_{A}$$

$$= [\mathbf{R}_{AB}^{-1}, -\mathbf{R}_{AB}^{-1} \mathbf{p}_{AB}] \mathbf{u}_{A}$$

$$= \mathbf{R}_{AB}^{-1} \mathbf{u}_{A} - \mathbf{R}_{AB}^{-1} \mathbf{p}_{AB}$$

$$= \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & -1 \\ -1 & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} - \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & -1 \\ -1 & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 & -1 \\ 1 & 0 & 0 \\ 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} - \begin{bmatrix} 0 & 0 & -1 \\ 1 & 0 & 0 \\ 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$= \begin{bmatrix} -6 \\ 4 \\ -5 \end{bmatrix} - \begin{bmatrix} -3 \\ 1 \\ -2 \end{bmatrix}$$

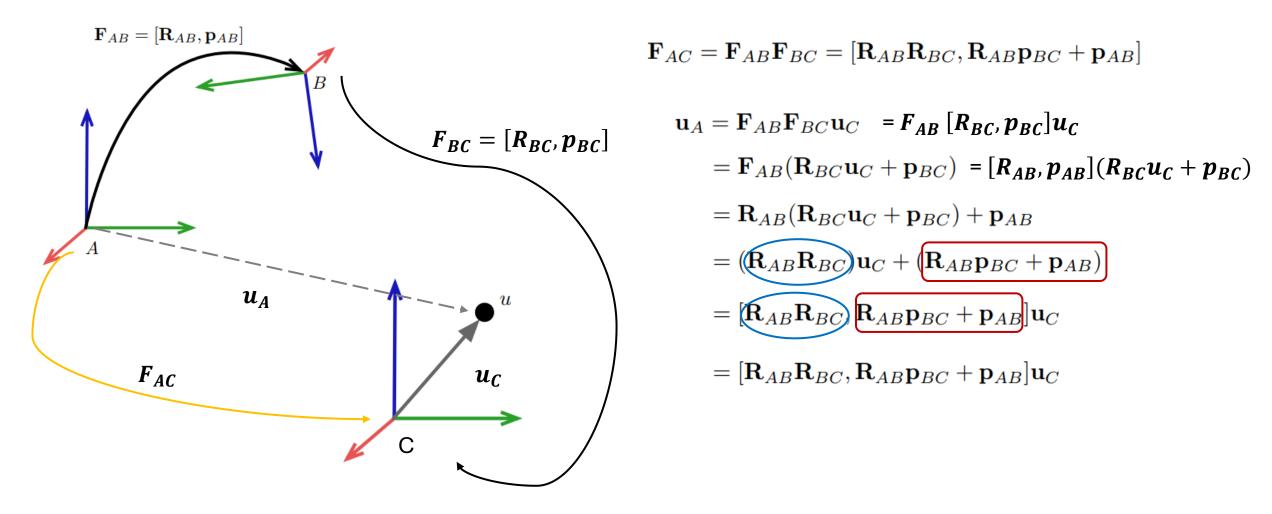
$$= \begin{bmatrix} -3 \\ 3 \\ -3 \end{bmatrix}$$

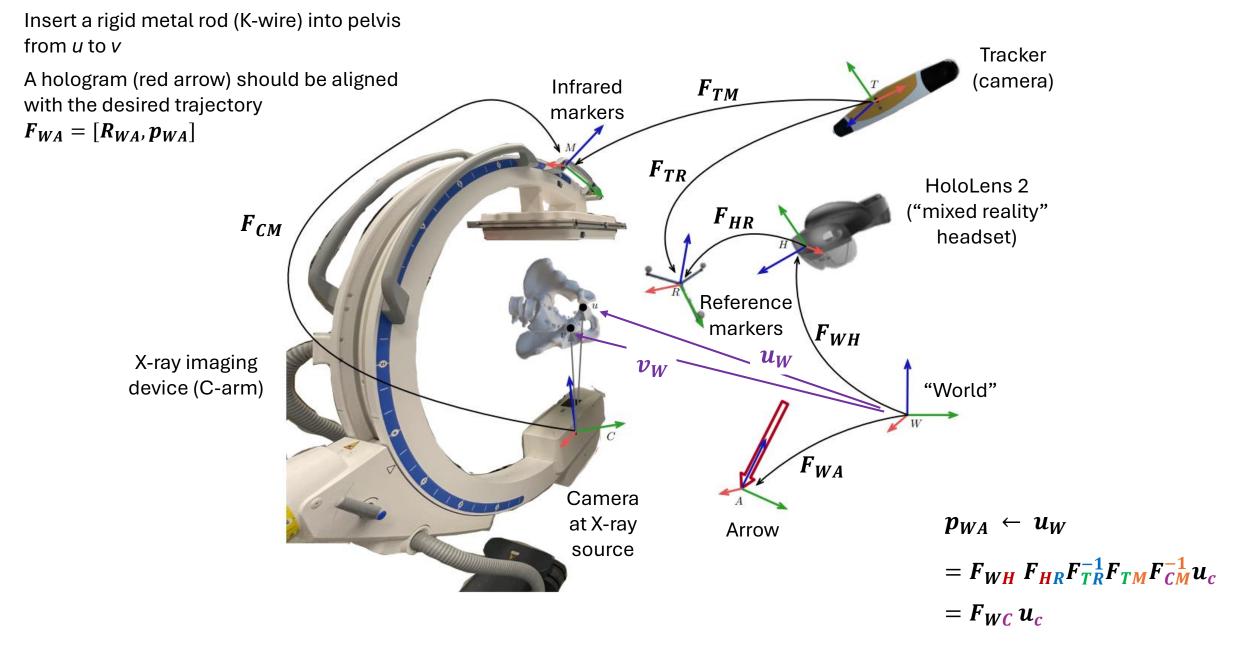
$$= \begin{bmatrix} -3 \\ 3 \\ -3 \end{bmatrix}$$

$$= \begin{bmatrix} -3 \\ 3 \\ -5 + 2 = -3 \end{bmatrix}$$

$$-5 + 2 = -3$$

#### **Frame Composition**





Benjamin D. Killeen (2022). Frame Transformations in Computer Integrated Surgery: A Graphical Introduction

$$\mathbf{p}_{WA} \leftarrow \mathbf{u}_W$$

$$= \mathbf{F}_{WH}\mathbf{F}_{HR}\mathbf{F}_{TR}^{-1}\mathbf{F}_{TM}\mathbf{F}_{CM}^{-1}\mathbf{u}_{C}$$

$$= [\mathbf{R}_{WH}, \mathbf{p}_{WH}][\mathbf{R}_{HR}, \mathbf{p}_{HR}][\mathbf{R}_{TR}^{-1}, -\mathbf{R}_{TR}^{-1}\mathbf{p}_{TR}][\mathbf{R}_{TM}, \mathbf{p}_{TM}][\mathbf{R}_{CM}^{-1}, -\mathbf{R}_{CM}^{-1}\mathbf{p}_{CM}]\mathbf{u}_{C}$$

$$= [\mathbf{R}_{WH}\mathbf{R}_{HR}\mathbf{R}_{TR}^{-1}\mathbf{R}_{TM}\mathbf{R}_{CM}^{-1}, -\mathbf{R}_{CM}^{-1}\mathbf{p}_{CM}] \mathbf{u}_{C}$$

$$- \mathbf{R}_{WH}\mathbf{R}_{HR}\mathbf{R}_{TR}^{-1}\mathbf{R}_{TM}\mathbf{R}_{CM}^{-1}\mathbf{p}_{CM}$$

$$+ \mathbf{R}_{WH}\mathbf{R}_{HR}\mathbf{R}_{TR}^{-1}\mathbf{p}_{TM}$$

$$- \mathbf{R}_{WH}\mathbf{R}_{HR}\mathbf{R}_{TR}^{-1}\mathbf{p}_{TM}$$

$$+ \mathbf{R}_{WH}\mathbf{p}_{HR}$$

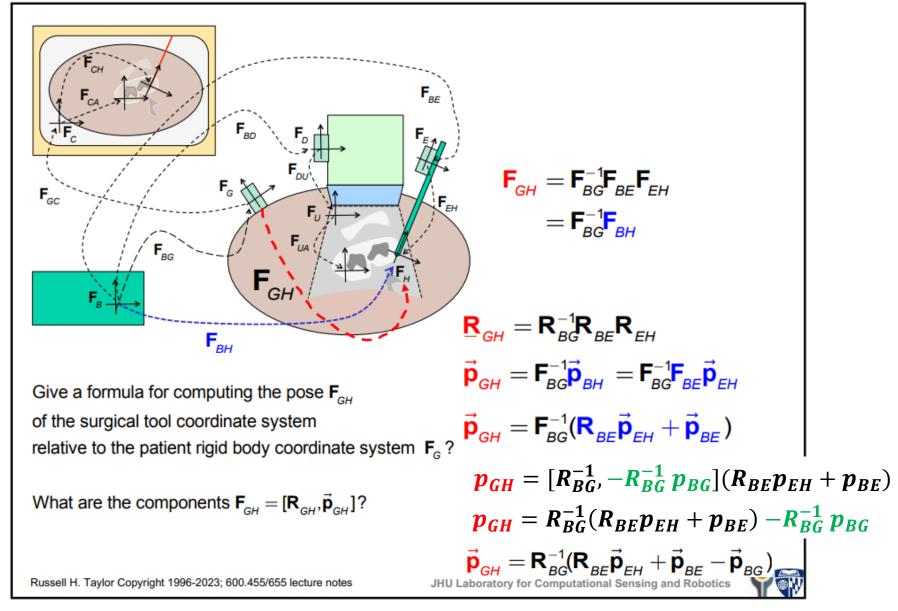
$$+ \mathbf{p}_{WH}\mathbf{u}_{C}$$

$$= \mathbf{F}_{WC}\mathbf{u}_{C}$$

$$= \mathbf{R}_{WC}\mathbf{u}_{C} + \mathbf{p}_{WC}$$

$$v_{W} = \mathbf{F}_{WC}\mathbf{v}_{C}$$

Similarly, we note  $\mathbf{v}_W = \mathbf{F}_{WC}\mathbf{v}_C$ .



#### Forward and Inverse Frame Transformations

# Forward Inverse $F = [R, \vec{p}]$ $F^{-1}\vec{v} = \vec{b}$ $\vec{b} = R^{-1} \bullet (\vec{v} - \vec{p})$ $= R^{-1} \bullet \vec{v} - R^{-1} \bullet \vec{p}$ $= [R, \vec{p}] \bullet \vec{b}$ $= [R, \vec{p}] \bullet \vec{b}$ $= R \bullet \vec{b} + \vec{p}$ $F^{-1} = [R^{-1}, -R^{-1} \bullet \vec{p}]$

#### Composition

Assume  $\mathbf{F}_1 = [\mathbf{R}_1, \vec{\mathbf{p}}_1], \quad \mathbf{F}_2 = [\mathbf{R}_2, \vec{\mathbf{p}}_2]$ Then

$$\begin{aligned} \mathbf{F}_{1} \bullet \mathbf{F}_{2} \bullet \vec{\mathbf{b}} &= \mathbf{F}_{1} \bullet (\mathbf{F}_{2} \bullet \vec{\mathbf{b}}) \\ &= \mathbf{F}_{1} \bullet (\mathbf{R}_{2} \bullet \vec{\mathbf{b}} + \vec{\mathbf{p}}_{2}) \\ &= [\mathbf{R}_{1}, \vec{\mathbf{p}}_{1}] \bullet (\mathbf{R}_{2} \bullet \vec{\mathbf{b}} + \vec{\mathbf{p}}_{2}) \\ &= \mathbf{R}_{1} \bullet (\mathbf{R}_{2} \bullet \vec{\mathbf{b}} + \vec{\mathbf{p}}_{2}) + \vec{\mathbf{p}}_{1} \\ &= \mathbf{R}_{1} \bullet \mathbf{R}_{2} \bullet \vec{\mathbf{b}} + \mathbf{R}_{1} \bullet \vec{\mathbf{p}}_{2} + \vec{\mathbf{p}}_{1} \\ &= [\mathbf{R}_{1} \bullet \mathbf{R}_{2}, \mathbf{R}_{1} \bullet \vec{\mathbf{p}}_{2} + \vec{\mathbf{p}}_{1}] \bullet \vec{\mathbf{b}} \end{aligned}$$

So

$$\mathbf{F}_{1} \bullet \mathbf{F}_{2} = [\mathbf{R}_{1}, \vec{\mathbf{p}}_{1}] \bullet [\mathbf{R}_{2}, \vec{\mathbf{p}}_{2}]$$
$$= [\mathbf{R}_{1} \bullet \mathbf{R}_{2}, \mathbf{R}_{1} \vec{\mathbf{p}}_{2} + \vec{\mathbf{p}}_{1}]$$

#### **Vectors**

# Matrix representation of cross product operator

dot product: 
$$\mathbf{a} = \vec{\mathbf{v}} \cdot \vec{\mathbf{w}} = (v_x w_x + v_y w_y + v_z w_z) = ||\vec{\mathbf{v}}|| ||\vec{\mathbf{w}}|| \cos \theta$$

cross product: 
$$\vec{\mathbf{u}} = \vec{\mathbf{v}} \times \vec{\mathbf{w}} = \begin{bmatrix} v_y w_z - v_z w_y \\ v_z w_x - v_x w_z \\ v_x w_y - v_y w_x \end{bmatrix}, \|\mathbf{u}\| = \|\mathbf{v}\| \|\mathbf{w}\| \sin \theta$$

Define

$$\hat{\vec{\mathbf{a}}} \stackrel{\triangle}{=} skew(\vec{\mathbf{a}}) \stackrel{\triangle}{=} \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix}$$

Then

$$\vec{\mathbf{a}} \times \vec{\mathbf{v}} = skew(\vec{\mathbf{a}}) \cdot \vec{\mathbf{v}}$$

Note that rotation doesn't affect inner products

$$(\mathbf{R} \bullet \vec{\mathbf{b}}) \bullet (\mathbf{R} \bullet \vec{\mathbf{c}}) = \vec{\mathbf{b}} \bullet \vec{\mathbf{c}}$$

or lengths of vectors

$$|\mathbf{R} \cdot \vec{\mathbf{v}}| = |\vec{\mathbf{v}}|$$

#### "Small" Frame Transformations

Represent a "small" pose shift consisting of a small rotation  $\Delta \mathbf{R}$  followed by a small displacement  $\Delta \vec{\mathbf{p}}$  as

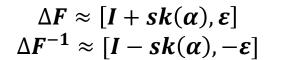
$$\Delta \mathbf{F} = [\Delta \mathbf{R}, \Delta \vec{\mathbf{p}}]$$

Then

$$\Delta \mathbf{F} \bullet \vec{\mathbf{v}} = \Delta \mathbf{R} \bullet \vec{\mathbf{v}} + \Delta \vec{\mathbf{p}}$$

# **Approximations to "Small" Frames**

$$\Delta \mathbf{R}(\vec{\mathbf{a}}) \approx \mathbf{I} + skew(\vec{\mathbf{a}})$$
  
 $\Delta \mathbf{R}(\vec{\mathbf{a}})^{-1} \approx \mathbf{I} - skew(\vec{\mathbf{a}}) = \mathbf{I} + skew(-\vec{\mathbf{a}})$ 



#### **Notational NOTE:**

We often use  $\vec{\alpha}$  to represent a vector of small angles and  $\vec{\varepsilon}$  to represent a vector of small displacements

In using these approximations, we typically ignore second order terms. I.e.,

$$\vec{\alpha}_A \vec{\alpha}_B \approx \vec{0}, \ \vec{\alpha}_A \vec{\varepsilon}_B \approx \vec{0}, \ \vec{\varepsilon}_A \vec{\varepsilon}_B \approx \vec{0}, \ \text{etc.}$$

# **Errors & sensitivity**

Often, we do not have an accurate value for a transformation, so we need to model the error. We model this as a composition of a "nominal" frame and a small displacement

$$\mathbf{F}_{\text{actual}} = \mathbf{F}_{\text{nominal}} \bullet \Delta \mathbf{F}$$

Often, we will use the notation  $\mathbf{F}^*$  for  $\mathbf{F}_{\text{actual}}$  and will just use  $\mathbf{F}$  for  $\mathbf{F}_{\text{nominal}}$ . Thus we may write something like

$$\mathbf{F}^{\star} = \mathbf{F} \bullet \Delta \mathbf{F}$$

or (less often)  $\mathbf{F}^* = \Delta \mathbf{F} \bullet \mathbf{F}$ . We also use  $\vec{\mathbf{v}}^* = \vec{\mathbf{v}} + \Delta \vec{\mathbf{v}}$ , etc. Thus, if we use the former form (error on the right), and have nominal relationship  $\vec{\mathbf{v}} = \mathbf{F} \bullet \vec{\mathbf{b}}$ , we get

$$\vec{\mathbf{v}}^* = \vec{\mathbf{F}}^* \bullet \vec{\mathbf{b}}^*$$

$$= \vec{\mathbf{F}} \bullet \Delta \vec{\mathbf{F}} \bullet (\vec{\mathbf{b}} + \Delta \vec{\mathbf{b}}) = \vec{\mathbf{F}} \bullet (\Delta \vec{\mathbf{R}} \bullet \vec{\mathbf{b}} + \Delta \vec{\mathbf{R}} \bullet \Delta \vec{\mathbf{b}} + \Delta \vec{\mathbf{p}})$$

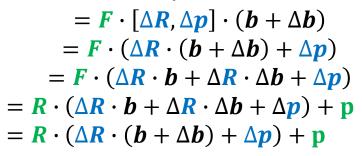
$$\approx \vec{\mathbf{R}} \bullet ((\vec{\mathbf{I}} + sk(\vec{\alpha})) \bullet (\vec{\mathbf{b}} + \Delta \vec{\mathbf{b}}) + \Delta \vec{\mathbf{p}}) + \vec{\mathbf{p}} = \vec{\mathbf{R}} \bullet (\vec{\mathbf{b}} + \vec{\alpha} \times \vec{\mathbf{b}} + \Delta \vec{\mathbf{b}} + \Delta \vec{\mathbf{p}}) + \vec{\mathbf{p}}$$

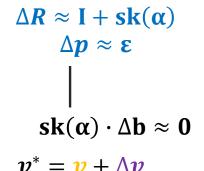
$$\approx \vec{\mathbf{R}} \bullet (\vec{\alpha} \times \vec{\mathbf{b}} + \Delta \vec{\mathbf{b}} + \Delta \vec{\mathbf{p}}) + \vec{\mathbf{R}} \bullet \vec{\mathbf{b}} + \vec{\mathbf{p}} = \vec{\mathbf{R}} \bullet (\vec{\alpha} \times \vec{\mathbf{b}} + \Delta \vec{\mathbf{b}} + \Delta \vec{\mathbf{p}}) + \vec{\mathbf{v}}$$

$$\Delta \vec{\mathbf{v}} \approx \vec{\mathbf{R}} \bullet (\vec{\alpha} \times \vec{\mathbf{b}} + \Delta \vec{\mathbf{b}} + \Delta \vec{\mathbf{p}})$$

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# Digression: "rotation triple product"

Expressions like  $\mathbf{R} \bullet \vec{\mathbf{a}} \times \vec{\mathbf{b}}$  are linear in  $\vec{\mathbf{a}}$ , but are not always convenient to work with. Often we would prefer something like  $\mathbf{M}(\mathbf{R}, \vec{\mathbf{b}}) \bullet \vec{\mathbf{a}}$ .

$$\mathbf{R} \bullet \vec{\mathbf{a}} \times \vec{\mathbf{b}} = -\mathbf{R} \bullet \vec{\mathbf{b}} \times \vec{\mathbf{a}}$$

$$= \mathbf{R} \bullet skew(-\vec{\mathbf{b}}) \bullet \vec{\mathbf{a}}$$

$$= \left[ \mathbf{R} \bullet skew(\vec{\mathbf{b}})^T \right] \bullet \vec{\mathbf{a}}$$

$$skew(\vec{\mathbf{a}}) \bullet \mathbf{R} = \mathbf{R} \bullet skew(\mathbf{R}^{-1} \bullet \vec{\mathbf{a}})$$
  
$$\mathbf{R}^{-1}skew(\vec{\mathbf{a}}) \bullet \mathbf{R} = skew(\mathbf{R}^{-1} \bullet \vec{\mathbf{a}})$$



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## A "standard form" for linearized error expressions

It is often convenient to use identities to rearrange expressions involving small error variables into sums of terms with the general form  $\mathbf{M}_k \vec{\eta}_k$ , where  $\mathbf{M}_k$  involve things known to the computer, and the  $\vec{\eta}_k$  are error variables.

For example,

$$\vec{\gamma} = \mathbf{R} s k(\vec{\alpha}) \vec{\mathbf{a}} + s k(\vec{\beta}) \vec{\mathbf{b}}$$

would be rewritten as

$$\vec{\gamma}$$
 =-**R**sk( $\vec{\mathbf{a}}$ ) $\vec{\alpha}$  - sk( $\vec{\mathbf{b}}$ ) $\vec{\beta}$ 

or

$$\vec{\gamma} = \mathbf{R} s k(-\vec{\mathbf{a}}) \vec{\alpha} + s k(-\vec{\mathbf{b}}) \vec{\beta}$$



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