# **Derivatives and Differentials**

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# Part I Theory

# 1 Optimization

We will be concerned with minimizing a non-linear least squares objective of the form

$$x^* = \arg\min_{x} ||h(x) - z||_{\Sigma}^2$$
 (1.1)

where  $x \in \mathcal{M}$  is a point on an *n*-dimensional manifold (which could be  $\mathbb{R}^n$ , an n-dimensional Lie group G, or a general manifold  $\mathcal{M}$ ),  $z \in \mathbb{R}^m$  is an observed measurement,  $h : \mathcal{M} \to \mathbb{R}^m$  is a measurement function that predicts z from x, and  $||e||_{\Sigma}^2 \stackrel{\Delta}{=} e^T \Sigma^{-1} e$  is the squared Mahalanobis distance with covariance  $\Sigma$ .

To minimize (1.1) we need a notion of how the non-linear measurement function h(x) behaves in the neighborhood of a linearization point a. Loosely speaking, we would like to define an  $m \times n$  Jacobian matrix  $H_a$  such that

$$h(a \oplus \xi) \approx h(a) + H_a \xi \tag{1.2}$$

with  $\xi \in \mathbb{R}^n$ , and the operation  $\oplus$  "increments"  $a \in \mathcal{M}$ . Below we more formally develop this notion, first for functions from  $\mathbb{R}^n \to \mathbb{R}^m$ , then for Lie groups, and finally for manifolds.

Once equipped with the approximation (1.2), we can minimize the objective function (1.1) with respect to  $\delta x$  instead:

$$\xi^* = \arg\min_{\xi} \|h(a) + H_a \xi - z\|_{\Sigma}^2$$
 (1.3)

This can be done by setting the derivative of (1.3) to zero, yielding the **normal equations**,

$$H_a^T H_a \xi = H_a^T (z - h(a))$$

which can be solved using Cholesky factorization. Of course, we might have to iterate this multiple times, and use a trust-region method to bound  $\xi$  when the approximation (1.2) is not good.

### 2 Multivariate Differentiation

#### 2.1 Derivatives

For a vector space  $\mathbb{R}^n$ , the notion of an increment is just done by vector addition

$$a \oplus \xi \stackrel{\Delta}{=} a + \xi$$

and for the approximation 1.2 we will use a Taylor expansion using multivariate differentiation. However, loosely following [4], we use a perhaps unfamiliar way to define derivatives:

**Definition 1.** We define a function  $f: \mathbb{R}^n \to \mathbb{R}^m$  to be **differentiable** at a if there exists a matrix  $f'(a) \in \mathbb{R}^{m \times n}$  such that

$$\lim_{\delta x \to 0} \frac{|f(a) + f'(a)\xi - f(a+\xi)|}{|\xi|} = 0$$

where  $|e| \stackrel{\Delta}{=} \sqrt{e^T e}$  is the usual norm. If f is differentiable, then the matrix f'(a) is called the **Jacobian matrix** of f at a, and the linear map  $Df_a: \xi \mapsto f'(a)\xi$  is called the **derivative** of f at a. When no confusion is likely, we use the notation  $F_a \stackrel{\Delta}{=} f'(a)$  to stress that f'(a) is a matrix.

The benefit of using this definition is that it generalizes the notion of a scalar derivative f'(a):  $\mathbb{R} \to \mathbb{R}$  to multivariate functions from  $\mathbb{R}^n \to \mathbb{R}^m$ . In particular, the derivative  $Df_a$  maps vector increments  $\xi$  on a to increments  $f'(a)\xi$  on f(a), such that this linear map locally approximates f:

$$f(a+\xi) \approx f(a) + f'(a)\xi$$

**Example 1.** The function  $\pi:(x,y,z)\mapsto(x/z,y/z)$  projects a 3D point (x,y,z) to the image plane, and has the Jacobian matrix

$$\pi'(x,y,z) = \frac{1}{z} \begin{bmatrix} 1 & 0 & -x/z \\ 0 & 1 & -y/z \end{bmatrix}$$

# 2.2 Properties of Derivatives

This notion of a multivariate derivative obeys the usual rules:

**Theorem 1.** (Chain rule) If  $f : \mathbb{R}^n \to \mathbb{R}^p$  is differentiable at a and  $g : \mathbb{R}^p \to \mathbb{R}^m$  is differentiable at f(a), then the Jacobian matrix  $H_a$  of  $h = g \circ f$  at a is the  $m \times n$  matrix product

$$H_a = G_{f(a)} F_a$$

*Proof.* See [4]  $\Box$ 

**Example 2.** If we follow the projection  $\pi$  by a calibration step  $\gamma:(x,y)\mapsto (u_0+fx,u_0+fy)$ , with

$$\gamma'(x,y) = \left[ \begin{array}{cc} f & 0 \\ 0 & f \end{array} \right]$$

then the combined function  $\gamma \circ \pi$  has the Jacobian matrix

$$(\gamma \circ \pi)'(x, y) = \frac{f}{z} \begin{bmatrix} 1 & 0 & -x/z \\ 0 & 1 & -y/z \end{bmatrix}$$

**Theorem 2.** (Inverse) If  $f: \mathbb{R}^n \to \mathbb{R}^n$  is differentiable and has a differentiable inverse  $g \stackrel{\Delta}{=} f^{-1}$ , then its Jacobian matrix  $G_a$  at a is just the inverse of that of f, evaluated at g(a):

$$G_a = \left[ F_{g(a)} \right]^{-1}$$

*Proof.* See [4]

**Example 3.** The function  $f:(x,y)\mapsto (x^2,xy)$  has the Jacobian matrix

$$F_{(x,y)} = \left[ \begin{array}{cc} 2x & 0 \\ y & x \end{array} \right]$$

and, for  $x \ge 0$ , its inverse is the function  $g:(x,y)\mapsto (x^{1/2},x^{-1/2}y)$  with the Jacobian matrix

$$G_{(x,y)} = \frac{1}{2} \begin{bmatrix} x^{-1/2} & 0 \\ -x^{-3/2}y & 2x^{-1/2} \end{bmatrix}$$

It is easily verified that

$$g'(a,b)f'(a^{1/2},a^{-1/2}b) = \frac{1}{2} \begin{bmatrix} a^{-1/2} & 0 \\ -a^{-3/2}b & 2a^{-1/2} \end{bmatrix} \begin{bmatrix} 2a^{1/2} & 0 \\ a^{-1/2}b & a^{1/2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

**Problem 1.** Verify the above for (a,b) = (4,6). Sketch the situation graphically to get insight.

#### 2.3 Computing Multivariate Derivatives

Computing derivatives is made easy by defining the concept of a partial derivative:

**Definition 2.** For  $f: \mathbb{R}^n \to \mathbb{R}$ , the **partial derivative** of f at a,

$$D_{j}f(a) \stackrel{\Delta}{=} \lim_{h \to 0} \frac{f\left(a^{1}, \dots, a^{j} + h, \dots, a^{n}\right) - f\left(a^{1}, \dots, a^{n}\right)}{h}$$

which is the ordinary derivative of the scalar function  $g(x) \stackrel{\Delta}{=} f(a^1, \dots, x, \dots, a^n)$ .

Using this definition, one can show that the Jacobian matrix  $F_a$  of a differentiable *multivariate* function  $f: \mathbb{R}^n \to \mathbb{R}^m$  consists simply of the  $m \times n$  partial derivatives  $D_i f^i(a)$ , evaluated at  $a \in \mathbb{R}^n$ :

$$F_a = \left[ \begin{array}{ccc} D_1 f^1(a) & \cdots & D_n f^1(a) \\ \vdots & \ddots & \vdots \\ D_1 f^m(a) & \cdots & D_n f^m(a) \end{array} \right]$$

**Problem 2.** Verify the derivatives in Examples 1 to 3.

# 3 Multivariate Functions on Lie Groups

#### 3.1 Lie Groups

Lie groups are not as easy to treat as the vector space  $\mathbb{R}^n$  but nevertheless have a lot of structure. To generalize the concept of the total derivative above we just need to replace  $a \oplus \xi$  in (1.3) with a suitable operation in the Lie group G. In particular, the notion of an exponential map allows us to define an incremental transformation as tracing out a geodesic curve on the group manifold along a certain **tangent vector**  $\xi$ ,

$$a \oplus \xi \stackrel{\Delta}{=} a \exp\left(\hat{\xi}\right)$$

with  $\xi \in \mathbb{R}^n$  for an *n*-dimensional Lie group,  $\hat{\xi} \in \mathfrak{g}$  the Lie algebra element corresponding to the vector  $\xi$ , and  $\exp \hat{\xi}$  the exponential map. Note that if G is equal to  $\mathbb{R}^n$  then composing with the exponential map  $ae^{\hat{\xi}}$  is just vector addition  $a + \xi$ .

**Example 4.** For the Lie group SO(3) of 3D rotations the vector  $\xi$  is denoted as  $\omega$  and represents an angular displacement. The Lie algebra element  $\hat{\xi}$  is a skew symmetric matrix denoted as  $[\omega]_{\times} \in \mathfrak{so}(3)$ , and is given by

$$[\boldsymbol{\omega}]_{\times} = \left[ egin{array}{ccc} 0 & -\omega_z & \omega_y \ \omega_z & 0 & -\omega_x \ -\omega_y & \omega_x & 0 \end{array} 
ight]$$

Finally, the increment  $a \oplus \xi = ae^{\hat{\xi}}$  corresponds to an incremental rotation  $R \oplus \omega = Re^{[\omega]_{\times}}$ .

#### 3.2 Derivatives

We can generalize Definition 1 to map exponential coordinates  $\xi$  to increments  $f'(a)\xi$  on f(a), such that the linear map  $Df_a$  locally approximates a function f from G to  $\mathbb{R}^m$ :

$$f(ae^{\hat{\xi}}) \approx f(a) + f'(a)\xi$$

**Definition 3.** We define a function  $f: G \to \mathbb{R}^m$  to be **differentiable** at  $a \in G$  if there exists a matrix  $f'(a) \in \mathbb{R}^{m \times n}$  such that

$$\lim_{\xi \to 0} \frac{\left| f(a) + f'(a)\xi - f(ae^{\hat{\xi}}) \right|}{|\xi|} = 0$$

If f is differentiable, then the matrix f'(a) is called the **Jacobian matrix** of f at a, and the linear map  $Df_a: \xi \mapsto f'(a)\xi$  is called the **derivative** of f at a.

Note that the vectors  $\xi$  can be viewed as lying in the tangent space to G at a, but defining this rigorously would take us on a longer tour of differential geometry. Informally,  $\xi$  is simply the direction, in a local coordinate frame, that is locally tangent at a to a geodesic curve  $\gamma: t \mapsto ae^{i\xi}$  traced out by the exponential map, with  $\gamma(0) = a$ .

#### 3.3 Derivative of an Action

The (usual) action of an *n*-dimensional matrix group *G* is matrix-vector multiplication on  $\mathbb{R}^n$ , i.e.,  $f: G \times \mathbb{R}^n \to \mathbb{R}^n$  with

$$f(T,p) = Tp$$

Since this is a function defined on the product  $G \times \mathbb{R}^n$  the derivative is a linear transformation  $Df : \mathbb{R}^{2n} \to \mathbb{R}^n$  with

$$Df_{(T,p)}(\xi, \delta p) = D_1 f_{(T,p)}(\xi) + D_2 f_{(T,p)}(\delta p)$$

**Theorem 3.** The Jacobian matrix of the group action f(T,P) = Tp at (T,p) is given by

$$F_{(T,p)} = \begin{bmatrix} TH(p) & T \end{bmatrix} = T \begin{bmatrix} H(p) & I_n \end{bmatrix}$$

with  $H: \mathbb{R}^n \to \mathbb{R}^{n \times n}$  a linear mapping that depends on p, and  $I_n$  the  $n \times n$  identity matrix.

*Proof.* First, the derivative  $D_2f$  with respect to in p is easy, as its matrix is simply T:

$$f(T, p + \delta p) = T(p + \delta p) = Tp + T\delta p = f(T, p) + D_2 f(\delta p)$$

For the derivative  $D_1 f$  with respect to a change in the first argument T, we want

$$f(Te^{\hat{\xi}}, p) = Te^{\hat{\xi}}p \approx Tp + D_1f(\xi)$$

Since the matrix exponential is given by the series  $e^A = I + A + \frac{A^2}{2!} + \frac{A^3}{3!} + \dots$  we have, to first order

$$Te^{\hat{\xi}}p \approx T(I+\hat{\xi})p = Tp + T\hat{\xi}p$$

Hence, we need to show that

$$\hat{\xi}p = H(p)\xi \tag{3.1}$$

with H(p) an  $n \times n$  matrix that depends on p. Expressing the map  $\xi \to \hat{\xi}$  in terms of the Lie algebra generators  $G^i$ , using tensors and Einstein summation, we have  $\hat{\xi}^i_j = G^i_{jk} \xi^k$  allowing us to calculate  $\hat{\xi}p$  as

$$\left(\hat{\xi}p\right)^{i} = \hat{\xi}^{i}_{j}p^{j} = G^{i}_{jk}\xi^{k}p^{j} = \left(G^{i}_{jk}p^{j}\right)\xi^{k} = H^{i}_{k}(p)\xi^{k}$$

**Example 5.** For 3D rotations  $R \in SO(3)$ , we have  $\hat{\omega} = [\omega]_{\times}$  and

$$G_{k=1}: \left( egin{array}{ccc} 0 & 0 & 0 & 0 \ 0 & 0 & -1 \ 0 & 1 & 0 \end{array} 
ight) G_{k=2}: \left( egin{array}{ccc} 0 & 0 & 1 \ 0 & 0 & 0 \ -1 & 0 & 0 \end{array} 
ight) \ G_{k=3}: \left( egin{array}{ccc} 0 & -1 & 0 \ 1 & 0 & 0 \ 0 & 0 & 0 \end{array} 
ight)$$

The matrices  $(G_k^i)_j$  are obtained by assembling the  $j^{th}$  columns of the generators above, yielding H(p) equal to:

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{pmatrix} p^1 + \begin{pmatrix} 0 & 0 & -1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} p^2 + \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} p^3 = \begin{pmatrix} 0 & p^3 & -p^2 \\ -p^3 & 0 & p^1 \\ p^2 & -p^1 & 0 \end{pmatrix} = [-p]_{\times}$$

Hence, the Jacobian matrix of f(R, p) = Rp is given by

$$F_{(R,p)} = R \left( \begin{array}{cc} [-p]_{\times} & I_3 \end{array} \right)$$

#### 3.4 Derivative of an Inverse Action

Applying the action by the inverse of  $T \in G$  yields a function  $g: G \times \mathbb{R}^n \to \mathbb{R}^n$  defined by

$$g(T,p) = T^{-1}p$$

**Theorem 4.** The Jacobian matrix of the inverse group action  $g(T,p) = T^{-1}p$  is given by

$$G_{(T,p)} = \begin{bmatrix} -H(T^{-1}p) & T^{-1} \end{bmatrix}$$

where  $H: \mathbb{R}^n \to \mathbb{R}^{n \times n}$  is the same mapping as before.

*Proof.* Again, the derivative  $D_2g$  with respect to in p is easy, the matrix of which is simply  $T^{-1}$ :

$$g(T, p + \delta p) = T^{-1}(p + \delta p) = T^{-1}p + T^{-1}\delta p = g(T, p) + D_2g(\delta p)$$

Conversely, a change in T yields

$$g(Te^{\hat{\xi}}, p) = \left(Te^{\hat{\xi}}\right)^{-1} p = e^{-\hat{\xi}} T^{-1} p$$

Similar to before, if we expand the matrix exponential we get

$$e^{-A} = I - A + \frac{A^2}{2!} - \frac{A^3}{3!} + \dots$$

so

$$e^{-\hat{\xi}}T^{-1}p \approx (I - \hat{\xi})T^{-1}p = g(T, p) - \hat{\xi}(T^{-1}p)$$

**Example 6.** For 3D rotations  $R \in SO(3)$  we have  $R^{-1} = R^T$ ,  $H(p) = -[p]_{\times}$ , and hence the Jacobian matrix of  $g(R, p) = R^T p$  is given by

$$G_{(R,p)} = ( [R^T p]_{\times} R^T )$$

# 4 Instantaneous Velocity

For matrix Lie groups, if we have a matrix  $T_b^n(t)$  that depends on a parameter t, i.e.,  $T_b^n(t)$  follows a curve on the manifold, then it would be of interest to find the velocity of a point  $q^n(t) = T_b^n(t)p^b$  acted upon by  $T_b^n(t)$ . We can express the velocity of q(t) in both the n-frame and b-frame:

$$\dot{q}^n = \dot{T}_b^n p^b = \dot{T}_b^n (T_b^n)^{-1} p^n$$
 and  $\dot{q}^b = (T_b^n)^{-1} \dot{q}^n = (T_b^n)^{-1} \dot{T}_b^n p^b$ 

Both the matrices  $\hat{\xi}_{nb}^n \stackrel{\triangle}{=} \dot{T}_b^n \left(T_b^n\right)^{-1}$  and  $\hat{\xi}_{nb}^b \stackrel{\triangle}{=} \left(T_b^n\right)^{-1} \dot{T}_b^n$  are skew-symmetric Lie algebra elements that describe the **instantaneous velocity** [3, page 51 for rotations, page 419 for SE(3)]. We will revisit this for both rotations and rigid 3D transformations.

# 5 Differentials: Smooth Mapping between Lie Groups

#### **5.1** Motivation and Definition

The above shows how to compute the derivative of a function  $f: G \to \mathbb{R}^m$ . However, what if the argument to f is itself the result of a mapping between Lie groups? In other words,  $f = g \circ \varphi$ , with  $g: G \to \mathbb{R}^m$  and where  $\varphi: H \to G$  is a smooth mapping from the n-dimensional Lie group H to the p-dimensional Lie group G. In this case, one would expect that we can arrive at  $Df_a$  by composing linear maps, as follows:

$$f'(a) = (g \circ \varphi)'(a) = G_{\varphi(a)} \varphi'(a)$$

where  $\varphi'(a)$  is an  $n \times p$  matrix that is the best linear approximation to the map  $\varphi : H \to G$ . The corresponding linear map  $D\varphi_a$  is called the **differential** or **pushforward** of the mapping  $\varphi$  at a.

Because a rigorous definition will lead us too far astray, here we only informally define the pushforward of  $\varphi$  at a as the linear map  $D\varphi_a: \mathbb{R}^n \to \mathbb{R}^p$  such that  $D\varphi_a(\xi) \stackrel{\Delta}{=} \varphi'(a)\xi$  and

$$\varphi\left(ae^{\xi}\right) \approx \varphi\left(a\right) \exp\left(\widehat{\varphi'(a)\xi}\right)$$
 (5.1)

with equality for  $\xi \to 0$ . We call  $\varphi'(a)$  the **Jacobian matrix** of the map  $\varphi$  at a. Below we show that even with this informal definition we can deduce the pushforward in a number of useful cases.

#### 5.2 Left Multiplication with a Constant

**Theorem 5.** Suppose G is an n-dimensional Lie group, and  $\varphi : G \to G$  is defined as  $\varphi(g) = hg$ , with  $h \in G$  a constant. Then  $D\varphi_a$  is the identity mapping and

$$\varphi'(a) = I_n$$

*Proof.* Defining  $y = D\varphi_a x$  as in (5.1), we have

$$\phi(a)e^{\hat{y}} = \phi(ae^{\hat{x}})$$

$$hae^{\hat{y}} = hae^{\hat{x}}$$

$$y = x$$

# **5.3** Pushforward of the Inverse Mapping

A well known property of Lie groups is the the fact that applying an incremental change  $\hat{\xi}$  in a different frame g can be applied in a single step by applying the change  $Ad_g\hat{\xi}$  in the original frame,

$$ge^{\hat{\xi}}g^{-1} = \exp\left(Ad_g\hat{\xi}\right) \tag{5.2}$$

where  $Ad_g: \mathfrak{g} \to \mathfrak{g}$  is the **adjoint representation**. This comes in handy in the following:

**Theorem 6.** Suppose that  $\varphi : G \to G$  is defined as the mapping from an element g to its **inverse**  $g^{-1}$ , i.e.,  $\varphi(g) = g^{-1}$ , then the pushforward  $D\varphi_a$  satisfies

$$(D\varphi_a x)\hat{} = -Ad_a \hat{x} \tag{5.3}$$

In other words, and this is intuitive in hindsight, approximating the inverse is accomplished by negation of  $\hat{\xi}$ , along with an adjoint to make sure it is applied in the right frame. Note, however, that (5.3) does not immediately yield a useful expression for the Jacobian matrix  $\varphi'(a)$ , but in many important cases this will turn out to be easy.

*Proof.* Defining  $y = D\varphi_a x$  as in (5.1), we have

$$\phi(a)e^{\hat{y}} = \phi(ae^{\hat{x}})$$

$$a^{-1}e^{\hat{y}} = (ae^{\hat{x}})^{-1}$$

$$e^{\hat{y}} = -ae^{\hat{x}}a^{-1}$$

$$\hat{y} = -Ad_a\hat{x}$$

**Example 7.** For 3D rotations  $R \in SO(3)$  we have

$$Ad_{g}(\hat{\boldsymbol{\omega}}) = R\hat{\boldsymbol{\omega}}R^{T} = [R\boldsymbol{\omega}]_{\times}$$

and hence the pushforward for the inverse mapping  $\varphi(R) = R^T$  has the matrix  $\varphi'(R) = -R$ .

#### 5.4 Right Multiplication with a Constant

**Theorem 7.** Suppose  $\varphi: G \to G$  is defined as  $\varphi(g) = gh$ , with  $h \in G$  a constant. Then  $D\varphi_a$  satisfies

$$(D\varphi_a x)^{\hat{}} = Ad_{h^{-1}}\hat{x}$$

*Proof.* Defining  $y = D\varphi_a x$  as in (5.1), we have

$$\phi(a)e^{\hat{y}} = \phi(ae^{\hat{x}})$$

$$ahe = ae^{\hat{x}}h$$

$$e^{\hat{y}} = h^{-1}e^{\hat{x}}h = \exp(Ad_{h^{-1}}\hat{x})$$

$$\hat{y} = Ad_{h^{-1}}\hat{x}$$

**Example 8.** In the case of 3D rotations, right multiplication with a constant rotation R is done through the mapping  $\varphi(A) = AR$ , and satisfies

$$[D\varphi_A x]_{\times} = Ad_{R^T}[x]_{\times}$$

For 3D rotations  $R \in SO(3)$  we have

$$Ad_{R^T}(\hat{\boldsymbol{\omega}}) = R^T \hat{\boldsymbol{\omega}} R = [R^T \boldsymbol{\omega}]_{\times}$$

and hence the Jacobian matrix of  $\varphi$  at A is  $\varphi'(A) = R^T$ .

#### 5.5 Pushforward of Compose

**Theorem 8.** *If we define the mapping*  $\varphi$  :  $G \times G \rightarrow G$  *as the product of two group elements*  $g, h \in G$ , *i.e.,*  $\varphi(g,h) = gh$ , *then the pushforward will satisfy* 

$$D\varphi_{(a,b)}(x,y) = D_1\varphi_{(a,b)}x + D_2\varphi_{(a,b)}y$$

with

$$(D_1 \varphi_{(a,b)} x)^{\hat{}} = Ad_{b^{-1}} \hat{x} \text{ and } D_2 \varphi_{(a,b)} y = y$$

*Proof.* Looking at the first argument, the proof is very similar to right multiplication with a constant b. Indeed, defining  $y = D\varphi_a x$  as in (5.1), we have

$$\begin{aligned} \phi(a,b)e^{\hat{y}} &= \phi(ae^{\hat{x}},b) \\ abe^{\hat{y}} &= ae^{\hat{x}}b \\ e^{\hat{y}} &= b^{-1}e^{\hat{x}}b = \exp\left(Ad_{b^{-1}}\hat{x}\right) \\ \hat{y} &= Ad_{b^{-1}}\hat{x} \end{aligned} \tag{5.4}$$

In other words, to apply an incremental change  $\hat{x}$  to a we first need to undo b, then apply  $\hat{x}$ , and then apply b again. Using (5.2) this can be done in one step by simply applying  $Ad_{b^{-1}}\hat{x}$ .

The second argument is quite a bit easier and simply yields the identity mapping:

$$\varphi(a,b)e^{\hat{y}} = \varphi(a,be^{\hat{x}})$$

$$abe^{\hat{y}} = abe^{\hat{x}}$$

$$y = x$$
(5.5)

**Example 9.** For 3D rotations  $A, B \in SO(3)$  we have  $\varphi(A, B) = AB$ , and  $Ad_{B^T}[\omega]_{\times} = [B^T \omega]_{\times}$ , hence the Jacobian matrix  $\varphi'(A, B)$  of composing two rotations is given by

$$\varphi'(A,B) = \begin{bmatrix} B^T & I_3 \end{bmatrix}$$

#### 5.6 Pushforward of Between

Finally, let us find the pushforward of **between**, defined as  $\varphi(g,h) = g^{-1}h$ . For the first argument we reason as:

$$\varphi(g,h)e^{\hat{y}} = \varphi(ge^{\hat{x}},h) 
g^{-1}he^{\hat{y}} = (ge^{\hat{x}})^{-1}h = -e^{\hat{x}}g^{-1}h 
e^{\hat{y}} = -(h^{-1}g)e^{\hat{x}}(h^{-1}g)^{-1} = -\exp Ad_{(h^{-1}g)}\hat{x} 
\hat{y} = -Ad_{(h^{-1}g)}\hat{x} = -Ad_{\varphi(h,g)}\hat{x}$$
(5.6)

The second argument yields the identity mapping.

**Example 10.** For 3D rotations  $A, B \in SO(3)$  we have  $\varphi(A, B) = A^T B$ , and  $Ad_{B^T A}[-\omega]_{\times} = [-B^T A\omega]_{\times}$ , hence the Jacobian matrix  $\varphi'(A, B)$  of between is given by

$$\varphi'(A,B) = [ (-B^T A) I_3 ]$$

#### 5.7 **Numerical PushForward**

Let's examine

$$f(g)e^{\hat{y}} = f(ge^{\hat{x}})$$

and multiply with  $f(g)^{-1}$  on both sides:

$$e^{\hat{y}} = f(g)^{-1} f\left(ge^{\hat{x}}\right)$$

We then take the log (which in our case returns y, not  $\hat{y}$ ):

$$y(x) = \log \left[ f(g)^{-1} f(ge^{\hat{x}}) \right]$$

Let us look at x = 0, and perturb in direction i,  $e_i = [0, 0, 1, 0, 0]$ . Then take derivative,

$$\frac{\partial y(d)}{\partial d} \stackrel{\Delta}{=} \lim_{d \to 0} \frac{y(d) - y(0)}{d} = \lim_{d \to 0} \frac{1}{d} \log \left[ f(g)^{-1} f\left(ge^{\widehat{de_i}}\right) \right]$$

which is the basis for a numerical derivative scheme.

#### **5.8 Derivative of the Exponential and Logarithm Map**

**Theorem 9.** The derivative of the function  $f: \mathbb{R}^n \to G$  that applies the wedge operator followed by the exponential map, i.e.,  $f(\xi) = \exp \hat{\xi}$ , is the identity map for  $\xi = 0$ .

*Proof.* For  $\xi = 0$ , we have

$$f(\xi)e^{\hat{y}} = f(\xi + x)$$
  
$$f(0)e^{\hat{y}} = f(0 + x)$$
  
$$e^{\hat{y}} = e^{\hat{x}}$$

**Corollary 1.** The derivative of the inverse  $f^{-1}$  is the identity as well, i.e., for T = e, the identity element in G.

For  $\xi \neq 0$ , things are not simple, see . http://deltaepsilons.wordpress.com/2009/11/ 06/helgasons-formula-for-the-differential-of-the-exponential/.

#### 6 General Manifolds

#### **6.1 Retractions**

General manifolds that are not Lie groups do not have an exponential map, but can still be handled by defining a **retraction**  $\mathscr{R}: \mathscr{M} \times \mathbb{R}^n \to \mathscr{M}$ , such that

$$a \oplus \xi \stackrel{\Delta}{=} \mathscr{R}_a(\xi)$$

A retraction [1] is required to be tangent to geodesics on the manifold  $\mathcal{M}$  at a. We can define many retractions for a manifold  $\mathcal{M}$ , even for those with more structure. For the vector space  $\mathbb{R}^n$  the retraction is just vector addition, and for Lie groups the obvious retraction is simply the exponential map, i.e.,  $\mathcal{R}_a(\xi) = a \cdot \exp \hat{\xi}$ . However, one can choose other, possibly computationally attractive retractions, as long as around a they agree with the geodesic induced by the exponential map, i.e.,

$$\lim_{\xi \to 0} \frac{\left| a \cdot \exp \hat{\xi} - \mathcal{R}_a(\xi) \right|}{|\xi|} = 0$$

**Example 11.** For SE(3), instead of using the true exponential map it is computationally more efficient to define the retraction, which uses a first order approximation of the translation update

$$\mathscr{R}_T\left(\left[\begin{array}{c} \boldsymbol{\omega} \\ \boldsymbol{v} \end{array}\right]\right) = \left[\begin{array}{cc} R & t \\ 0 & 1 \end{array}\right] \left[\begin{array}{cc} e^{[\boldsymbol{\omega}]_{\times}} & \boldsymbol{v} \\ 0 & 1 \end{array}\right] = \left[\begin{array}{cc} Re^{[\boldsymbol{\omega}]_{\times}} & t + R\boldsymbol{v} \\ 0 & 1 \end{array}\right]$$

#### **6.2** Derivatives

Equipped with a retraction, then, we can generalize the notion of a derivative for functions f from general a manifold  $\mathcal{M}$  to  $\mathbb{R}^m$ :

**Definition 4.** We define a function  $f: \mathcal{M} \to \mathbb{R}^m$  to be **differentiable** at  $a \in \mathcal{M}$  if there exists a matrix f'(a) such that

$$\lim_{\xi \to 0} \frac{|f(a) + f'(a)\xi - f(\mathcal{R}_a(\xi))|}{|\xi|} = 0$$

with  $\xi \in \mathbb{R}^n$  for an *n*-dimensional manifold, and  $\mathcal{R}_a : \mathbb{R}^n \to \mathcal{M}$  a retraction  $\mathcal{R}$  at a. If f is differentiable, then f'(a) is called the **Jacobian matrix** of f at a, and the linear transformation  $Df_a : \xi \mapsto f'(a)\xi$  is called the **derivative** of f at a.

For manifolds that are also Lie groups, the derivative of any function  $f: G \to \mathbb{R}^m$  will agree no matter what retraction  $\mathscr{R}$  is used.

#### Part II

# **Practice**

Below we apply the results derived in the theory part to the geometric objects we use in GTSAM. Above we preferred the modern notation  $D_1f$  for the partial derivative. Below (because this was written earlier) we use the more classical notation

$$\frac{\partial f(x,y)}{\partial x}$$

In addition, for Lie groups we will abuse the notation and take

$$\frac{\partial \varphi(g)}{\partial \xi}\bigg|_a$$

to be the Jacobian matrix  $\varphi'(a)$  of the mapping  $\varphi$  at  $a \in G$ , associated with the pushforward  $D\varphi_a$ .

# 7 SLAM Example

Let us examine a visual SLAM example. We have 2D measurements  $z_{ij}$ , where each measurement is predicted by

$$z_{ij} = h(T_i, p_j) = \pi(T_i^{-1}p_j)$$

where  $T_i$  is the 3D pose of the  $i^{th}$  camera,  $p_j$  is the location of the  $j^{th}$  point, and  $\pi:(x,y,z)\mapsto (x/z,y/z)$  is the camera projection function from Example 1.

# 8 BetweenFactor

BetweenFactor is often used to summarize

Theorem 9 about the derivative of the exponential map  $f: \xi \mapsto \exp \hat{\xi}$  being identity only at  $\xi = 0$  has implications for GTSAM. Given two elements  $T_1$  and  $T_2$ , BetweenFactor evaluates

$$g(T_1, T_2; Z) = f^{-1} \left( between(Z, between(T_1, T_2)) = f^{-1} \left( Z^{-1} \left( T_1^{-1} T_2 \right) \right) \right)$$

but because it is assumed that  $Z \approx T_1^{-1}T_2$ , and hence we have  $Z^{-1}T_1^{-1}T_2 \approx e$  and the derivative should be good there. Note that the derivative of *between* is identity in its second argument.

# 9 Point3

A cross product  $a \times b$  can be written as a matrix multiplication

$$a \times b = [a]_{\times} b$$

where  $[a]_{\times}$  is a skew-symmetric matrix defined as

$$[x,y,z]_{\times} = \begin{bmatrix} 0 & -z & y \\ z & 0 & -x \\ -y & x & 0 \end{bmatrix}$$

We also have

$$a^{T}[b]_{\times} = -([b]_{\times}a)^{T} = -(a \times b)^{T}$$

The derivative of a cross product

$$\frac{\partial (a \times b)}{\partial a} = [-b]_{\times} \tag{9.1}$$

$$\frac{\partial (a \times b)}{\partial b} = [a]_{\times} \tag{9.2}$$

### 10 2D Rotations

#### 10.1 Rot2 in GTSAM

A rotation is stored as  $(\cos \theta, \sin \theta)$ . An incremental rotation is applied using the trigonometric sum rule:

$$\cos \theta' = \cos \theta \cos \delta - \sin \theta \sin \delta$$

$$\sin \theta' = \sin \theta \cos \delta + \cos \theta \sin \delta$$

where  $\delta$  is an incremental rotation angle.

#### **10.2** Derivatives of Actions

In the case of SO(2) the vector space is  $\mathbb{R}^2$ , and the group action f(R,p) corresponds to rotating the 2D point p

$$f(R,p) = Rp$$

According to Theorem 3, the Jacobian matrix of f is given by

$$f'(R,p) = [RH(p) R]$$

with  $H: \mathbb{R}^2 \to \mathbb{R}^{2\times 2}$  a linear mapping that depends on p. In the case of SO(2), we can find H(p) by equating (as in Equation 3.1):

$$[w]_+ p = \begin{bmatrix} 0 & -\omega \\ \omega & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -y \\ x \end{bmatrix} \omega = H(p)\omega$$

Note that

$$H(p) = \begin{bmatrix} -y \\ x \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = R_{\pi/2}p$$

and since 2D rotations commute, we also have, with q = Rp:

$$f'(R,p) = \left[ \begin{array}{cc} R \left( R_{\pi/2} p \right) & R \end{array} \right] = \left[ \begin{array}{cc} R_{\pi/2} q & R \end{array} \right]$$

# 10.3 Pushforwards of Mappings

Since  $Ad_R[\omega]_+ = [\omega]_+$ , we have the derivative of **inverse**,

$$\frac{\partial R^T}{\partial \omega} = -Ad_R = -1$$

compose,

$$\frac{\partial (R_1 R_2)}{\partial \omega_1} = A d_{R_2^T} = 1 \text{ and } \frac{\partial (R_1 R_2)}{\partial \omega_2} = 1$$

and between:

$$\frac{\partial \left(R_1^T R_2\right)}{\partial \omega_1} = -A d_{R_2^T R_1} = -1 \text{ and } \frac{\partial \left(R_1^T R_2\right)}{\partial \omega_2} = 1$$

# 11 2D Rigid Transformations

#### 11.1 The derivatives of Actions

The action of SE(2) on 2D points is done by embedding the points in  $\mathbb{R}^3$  by using homogeneous coordinates

$$f(T,p) = \hat{q} = \begin{bmatrix} q \\ 1 \end{bmatrix} = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} p \\ 1 \end{bmatrix} = T\hat{p}$$

To find the derivative, we write the quantity  $\hat{\xi}\hat{p}$  as the product of the 3 × 3 matrix H(p) with  $\xi$ :

$$\hat{\xi}\hat{p} = \begin{bmatrix} [\omega]_{+} & v \\ 0 & 0 \end{bmatrix} \begin{bmatrix} p \\ 1 \end{bmatrix} = \begin{bmatrix} [\omega]_{+}p + v \\ 0 \end{bmatrix} = \begin{bmatrix} I_{2} & R_{\pi/2}p \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} = H(p)\xi$$
 (11.1)

Hence, by Theorem 3 we have

$$\frac{\partial \left(T\hat{p}\right)}{\partial \xi} = TH(p) = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_2 & R_{\pi/2}p \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R & RR_{\pi/2}p \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R & R_{\pi/2}q \\ 0 & 0 \end{bmatrix} \tag{11.2}$$

Note that, looking only at the top rows of (11.1) and (11.2), we can recognize the quantity  $[\omega]_+p+v=v+\omega\left(R_{\pi/2}p\right)$  as the velocity of p in  $\mathbb{R}^2$ , and  $\begin{bmatrix}R&R_{\pi/2}q\end{bmatrix}$  is the derivative of the action on  $\mathbb{R}^2$ .

The derivative of the inverse action  $g(T, p) = T^{-1}\hat{p}$  is given by Theorem 4 specialized to SE(2):

$$\frac{\partial \left(T^{-1}\hat{p}\right)}{\partial \xi} = -H(T^{-1}p) = \begin{bmatrix} -I_2 & -R_{\pi/2} \left(T^{-1}p\right) \\ 0 & 0 \end{bmatrix}$$

# 11.2 Pushforwards of Mappings

We can just define all derivatives in terms of the adjoint map, which in the case of SE(2), in twist coordinates, is the linear mapping

$$Ad_T \xi = \left[ \begin{array}{cc} R & -R_{\pi/2}t \\ 0 & 1 \end{array} \right] \left[ \begin{array}{c} v \\ \omega \end{array} \right]$$

and we have

$$\frac{\partial T^{-1}}{\partial \xi} = -Ad_T$$

$$\frac{\partial (T_1 T_2)}{\partial \xi_1} = Ad_{T_2^{-1}} \text{ and } \frac{\partial (T_1 T_2)}{\partial \xi_2} = I_3$$

$$\frac{\partial (T_1^{-1}T_2)}{\partial \xi_1} = -Ad_{T_2^{-1}T_1} = -Ad_{between(T_2,T_1)} \text{ and } \frac{\partial (T_1^{-1}T_2)}{\partial \xi_2} = I_3$$

### 12 3D Rotations

#### **12.1** Derivatives of Actions

In the case of SO(3) the vector space is  $\mathbb{R}^3$ , and the group action f(R,p) corresponds to rotating a point

$$q = f(R, p) = Rp$$

To calculate H(p) for use in Theorem (3) we make use of

$$[\boldsymbol{\omega}]_{\times} p = \boldsymbol{\omega} \times p = -p \times \boldsymbol{\omega} = [-p]_{\times} \boldsymbol{\omega}$$

so  $H(p) \stackrel{\Delta}{=} [-p]_{\times}$ . Hence, the final derivative of an action in its first argument is

$$\frac{\partial (Rp)}{\partial \omega} = RH(p) = -R[p]_{\times}$$

Likewise, according to Theorem 4, the derivative of the inverse action is given by

$$\frac{\partial \left(R^T p\right)}{\partial \omega} = -H(R^T p) = [R^T p]_{\times}$$

#### 12.2 Instantaneous Velocity

For 3D rotations  $R_b^n$  from a body frame b to a navigation frame n we have the spatial angular velocity  $\omega_{nb}^n$  measured in the navigation frame,

$$[\boldsymbol{\omega}_{nh}^n]_{\times} \stackrel{\Delta}{=} \dot{R}_h^n (R_h^n)^T = \dot{R}_h^n R_n^b$$

and the body angular velocity  $\omega_{nb}^b$  measured in the body frame:

$$[\boldsymbol{\omega}_{nb}^b]_{\times} \stackrel{\Delta}{=} (\boldsymbol{R}_b^n)^T \dot{\boldsymbol{R}}_b^n = \boldsymbol{R}_n^b \dot{\boldsymbol{R}}_b^n$$

These quantities can be used to derive the velocity of a point p, and we choose between spatial or body angular velocity depending on the frame in which we choose to represent p:

$$v^n = [\boldsymbol{\omega}_{nb}^n]_{\times} p^n = \boldsymbol{\omega}_{nb}^n \times p^n$$

$$v^b = [\omega^b_{nb}]_{\times} p^b = \omega^b_{nb} \times p^b$$

We can transform these skew-symmetric matrices from navigation to body frame by conjugating,

$$[\omega_{nb}^b]_{\times} = R_n^b [\omega_{nb}^n]_{\times} R_b^n$$

but because the adjoint representation satisfies

$$Ad_R[\boldsymbol{\omega}]_{\times} \stackrel{\Delta}{=} R[\boldsymbol{\omega}]_{\times} R^T = [R\boldsymbol{\omega}]_{\times}$$

we can even more easily transform between spatial and body angular velocities as 3-vectors:

$$\omega_{nb}^b = R_n^b \omega_{nb}^n$$

#### 12.3 Pushforwards of Mappings

For SO(3) we have  $Ad_R[\omega]_{\times} = [R\omega]_{\times}$  and, in terms of angular velocities:  $Ad_R\omega = R\omega$ . Hence, the Jacobian matrix of the **inverse** mapping is (see Equation 5.3)

$$\frac{\partial R^T}{\partial \omega} = -Ad_R = -R$$

for **compose** we have (Equations 5.4 and 5.5):

$$\frac{\partial (R_1 R_2)}{\partial \omega_1} = R_2^T \text{ and } \frac{\partial (R_1 R_2)}{\partial \omega_2} = I_3$$

and **between** (Equation 5.6):

$$\frac{\partial \left(R_1^T R_2\right)}{\partial \omega_1} = -R_2^T R_1 = -between(R_2, R_1) \text{ and } \frac{\partial \left(R_1 R_2\right)}{\partial \omega_2} = I_3$$

#### 12.4 Retractions

Absil [1, page 58] discusses two possible retractions for SO(3) based on the QR decomposition or the polar decomposition of the matrix  $R[\omega]_{\times}$ , but they are expensive. Another retraction is based on the Cayley transform  $\mathscr{C} : \mathfrak{so}(3) \to SO(3)$ , a mapping from the skew-symmetric matrices to rotation matrices:

$$Q = \mathscr{C}(\Omega) = (I - \Omega)(I + \Omega)^{-1}$$

Interestingly, the inverse Cayley transform  $\mathscr{C}^{-1}:SO(3)\to\mathfrak{so}(3)$  has the same form:

$$\Omega = \mathcal{C}^{-1}(Q) = (I - Q)(I + Q)^{-1}$$

The retraction needs a factor  $-\frac{1}{2}$  however, to make it locally align with a geodesic:

$$R' = \mathscr{R}_R(\boldsymbol{\omega}) = R\mathscr{C}(-\frac{1}{2}[\boldsymbol{\omega}]_{\times})$$

Note that given  $\omega = (x, y, z)$  this has the closed-form expression below

$$\frac{1}{4+x^2+y^2+z^2} \begin{bmatrix} 4+x^2-y^2-z^2 & 2xy-4z & 2xz+4y \\ 2xy+4z & 4-x^2+y^2-z^2 & 2yz-4x \\ 2xz-4y & 2yz+4x & 4-x^2-y^2+z^2 \end{bmatrix}$$

$$= \frac{1}{4+x^2+y^2+z^2} \left\{ 4(I+[\omega]_{\times}) + \begin{bmatrix} x^2-y^2-z^2 & 2xy & 2xz \\ 2xy & -x^2+y^2-z^2 & 2yz \\ 2xz & 2yz & -x^2-y^2+z^2 \end{bmatrix} \right\}$$

so it can be seen to be a second-order correction on  $(I + [\omega]_{\times})$ . The corresponding approximation to the logarithmic map is:

$$[\omega]_{\times} = \mathscr{R}_R^{-1}(R') = -2\mathscr{C}^{-1}(R^T R')$$

# 13 3D Rigid Transformations

#### 13.1 The derivatives of Actions

The action of SE(3) on 3D points is done by embedding the points in  $\mathbb{R}^4$  by using homogeneous coordinates

$$\hat{q} = \left[ \begin{array}{c} q \\ 1 \end{array} \right] = f(T,p) = \left[ \begin{array}{cc} R & t \\ 0 & 1 \end{array} \right] \left[ \begin{array}{c} p \\ 1 \end{array} \right] = T\hat{p}$$

The quantity  $\hat{\xi}\hat{p}$  corresponds to a velocity in  $\mathbb{R}^4$  (in the local T frame), and equating it to  $H(p)\xi$  as in Equation 3.1 yields the  $4 \times 6$  matrix  $H(p)^1$ :

$$\hat{\xi}\hat{p} = \left[ \begin{array}{cc} [\boldsymbol{\omega}]_{\times} & v \\ 0 & 0 \end{array} \right] \left[ \begin{array}{c} p \\ 1 \end{array} \right] = \left[ \begin{array}{cc} \boldsymbol{\omega} \times p + v \\ 0 \end{array} \right] = \left[ \begin{array}{cc} [-p]_{\times} & I_{3} \\ 0 & 0 \end{array} \right] \left[ \begin{array}{c} \boldsymbol{\omega} \\ v \end{array} \right] = H(p)\xi$$

Note how velocities are analogous to points at infinity in projective geometry: they correspond to free vectors indicating a direction and magnitude of change. According to Theorem 3, the derivative of the group action is then

$$\frac{\partial (T\hat{p})}{\partial \xi} = TH(p) = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} [-p]_{\times} & I_3 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R[-p]_{\times} & R \\ 0 & 0 \end{bmatrix}$$
$$\frac{\partial (T\hat{p})}{\partial \hat{p}} = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix}$$

in homogenous coordinates. In  $\mathbb{R}^3$  this becomes  $R \left[ -[p]_{\times} I_3 \right]$ .

The derivative of the inverse action  $T^{-1}p$  is given by Theorem 4:

$$\frac{\partial \left(T^{-1}\hat{p}\right)}{\partial \xi} = -H\left(T^{-1}\hat{p}\right) = \begin{bmatrix} [T^{-1}\hat{p}]_{\times} & -I_{3} \end{bmatrix}$$
$$\frac{\partial \left(T^{-1}\hat{p}\right)}{\partial \hat{p}} = \begin{bmatrix} R^{T} & -R^{T}t \\ 0 & 1 \end{bmatrix}$$

**Example 12.** Let us examine a visual SLAM example. We have 2D measurements  $z_{ij}$ , where each measurement is predicted by

$$z_{ij} = h(T_i, p_j) = \pi(T_i^{-1}p_j) = \pi(q)$$

where  $T_i$  is the 3D pose of the  $i^{th}$  camera,  $p_j$  is the location of the  $j^{th}$  point,  $q=(x',y',z')=T^{-1}p$  is the point in camera coordinates, and  $\pi:(x,y,z)\mapsto(x/z,y/z)$  is the camera projection function from Example 1. By the chain rule, we then have

$$\frac{\partial h(T,p)}{\partial \xi} = \frac{\partial \pi(q)}{\partial q} \frac{\partial (T^{-1}p)}{\partial \xi} = \frac{1}{z'} \begin{bmatrix} 1 & 0 & -x'/z' \\ 0 & 1 & -y'/z' \end{bmatrix} \begin{bmatrix} [q]_{\times} & -I_3 \end{bmatrix} = \begin{bmatrix} \pi'(q)[q]_{\times} & -\pi'(q) \end{bmatrix}$$
$$\frac{\partial h(T,p)}{\partial p} = \pi'(q)R^{T}$$

 $<sup>^{1}</sup>H(p)$  can also be obtained by taking the  $j^{th}$  column of each of the 6 generators to multiply with components of  $\hat{p}$ 

# 13.2 Instantaneous Velocity

For rigid 3D transformations  $T_b^n$  from a body frame b to a navigation frame n we have the instantaneous spatial twist  $\xi_{nb}^n$  measured in the navigation frame,

$$\hat{\xi}_{nb}^n \stackrel{\Delta}{=} \dot{T}_b^n \left( T_b^n \right)^{-1}$$

and the instantaneous body twist  $\xi_{nb}^b$  measured in the body frame:

$$\hat{\xi}_{nh}^b \stackrel{\Delta}{=} (T_h^n)^T \dot{T}_h^n$$

# 13.3 Pushforwards of Mappings

As we can express the Adjoint representation in terms of twist coordinates, we have

$$\left[\begin{array}{c} \boldsymbol{\omega}' \\ \boldsymbol{v}' \end{array}\right] = \left[\begin{array}{cc} R & 0 \\ [t]_{\times} R & R \end{array}\right] \left[\begin{array}{c} \boldsymbol{\omega} \\ \boldsymbol{v} \end{array}\right]$$

Hence, as with SO(3), we are now in a position to simply posit the derivative of **inverse**,

$$\frac{\partial T^{-1}}{\partial \xi} = -Ad_T = -\begin{bmatrix} R & 0\\ [t]_{\times} R & R \end{bmatrix}$$

compose in its first argument,

$$\frac{\partial \left(T_1 T_2\right)}{\partial \xi_1} = A d_{T_2^{-1}}$$

in its second argument,

$$\frac{\partial \left(T_1 T_2\right)}{\partial \xi_2} = I_6$$

between in its first argument,

$$\frac{\partial \left(T_1^{-1}T_2\right)}{\partial \xi_1} = -Ad_{T_2^{-1}T_1}$$

and in its second argument,

$$\frac{\partial \left(T_1^{-1}T_2\right)}{\partial \xi_1} = I_6$$

#### 13.4 Retractions

For SE(3), instead of using the true exponential map it is computationally more efficient to design other retractions. A first-order approximation to the exponential map does not quite cut it, as it

yields a  $4 \times 4$  matrix which is not in SE(3):

$$T \exp \hat{\xi} \approx T(I + \hat{\xi})$$

$$= T \left( I_4 + \begin{bmatrix} [\omega]_{\times} & v \\ 0 & 0 \end{bmatrix} \right)$$

$$= \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_3 + [\omega]_{\times} & v \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} R(I_3 + [\omega]_{\times}) & t + Rv \\ 0 & 1 \end{bmatrix}$$

However, we can make it into a retraction by using any retraction defined for SO(3), including, as below, using the exponential map  $Re^{[\omega]_{\times}}$ :

$$\mathscr{R}_T\left(\left[\begin{array}{c} \boldsymbol{\omega} \\ \boldsymbol{v} \end{array}\right]\right) = \left[\begin{array}{cc} R & t \\ 0 & 1 \end{array}\right] \left[\begin{array}{cc} e^{[\boldsymbol{\omega}]_{\times}} & \boldsymbol{v} \\ 0 & 1 \end{array}\right] = \left[\begin{array}{cc} Re^{[\boldsymbol{\omega}]_{\times}} & t + R\boldsymbol{v} \\ 0 & 1 \end{array}\right]$$

Similarly, for a second order approximation we have

$$T \exp \hat{\xi} \approx T(I + \hat{\xi} + \frac{\hat{\xi}^2}{2})$$

$$= T\left(I_4 + \begin{bmatrix} [\omega]_{\times} & v \\ 0 & 0 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} [\omega]_{\times} & v \\ 0 & 0 \end{bmatrix} \begin{bmatrix} [\omega]_{\times} & v \\ 0 & 0 \end{bmatrix} \right)$$

$$= \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \left( \begin{bmatrix} I_3 + [\omega]_{\times} + \frac{1}{2} [\omega]_{\times}^2 & v + \frac{1}{2} [\omega]_{\times} v \\ 0 & 1 \end{bmatrix} \right)$$

$$= \begin{bmatrix} R(I_3 + [\omega]_{\times} + \frac{1}{2} [\omega]_{\times}^2) & t + R[v + (\omega \times v)/2] \\ 0 & 1 \end{bmatrix}$$

inspiring the retraction

$$\mathscr{R}_T\left(\left[\begin{array}{c}\boldsymbol{\omega}\\\boldsymbol{v}\end{array}\right]\right) = \left[\begin{array}{cc}R & t\\0 & 1\end{array}\right] \left[\begin{array}{cc}e^{[\boldsymbol{\omega}]\times} & \boldsymbol{v} + (\boldsymbol{\omega}\times\boldsymbol{v})/2\\0 & 1\end{array}\right] = \left[\begin{array}{cc}Re^{[\boldsymbol{\omega}]\times} & t + R\left[\boldsymbol{v} + (\boldsymbol{\omega}\times\boldsymbol{v})/2\right]\\0 & 1\end{array}\right]$$

# **14 2D Line Segments (Ocaml)**

The error between an infinite line (a,b,c) and a 2D line segment ((x1,y1),(x2,y2)) is defined in Line3.ml.

# 15 Line3vd (Ocaml)

One representation of a line is through 2 vectors (v,d), where v is the direction and the vector d points from the origin to the closest point on the line.

In this representation, transforming a 3D line from a world coordinate frame to a camera at  $(R_w^c, t^w)$  is done by

$$v^{c} = R_{w}^{c} v^{w}$$
$$d^{c} = R_{w}^{c} (d^{w} + (t^{w} v^{w}) v^{w} - t^{w})$$

# 16 Line3 (Ocaml)

For 3D lines, we use a parameterization due to C.J. Taylor, using a rotation matrix R and 2 scalars a and b. The line direction v is simply the Z-axis of the rotated frame, i.e.,  $v = R_3$ , while the vector d is given by  $d = aR_1 + bR_2$ .

Now, we will *not* use the incremental rotation scheme we used for rotations: because the matrix R translates from the line coordinate frame to the world frame, we need to apply the incremental rotation on the right-side:

$$R' = R(I + \Omega)$$

Projecting a line to 2D can be done easily, as both *v* and *d* are also the 2D homogenous coordinates of two points on the projected line, and hence we have

$$l = v \times d$$

$$= R_3 \times (aR_1 + bR_2)$$

$$= a(R_3 \times R_1) + b(R_3 \times R_2)$$

$$= aR_2 - bR_1$$

This can be written as a rotation of a point,

$$l = R \begin{pmatrix} -b \\ a \\ 0 \end{pmatrix}$$

but because the incremental rotation is now done on the right, we need to figure out the derivatives again:

$$\frac{\partial (R(I+\Omega)x)}{\partial \omega} = \frac{\partial (R\Omega x)}{\partial \omega} = R \frac{\partial (\Omega x)}{\partial \omega} = R[-x]_{\times}$$
 (16.1)

and hence the derivative of the projection l with respect to the rotation matrix Rof the 3D line is

$$\frac{\partial(l)}{\partial\omega} = R\left[\begin{pmatrix} b \\ -a \\ 0 \end{pmatrix}\right]_{\times} = \begin{bmatrix} aR_3 & bR_3 & -(aR_1 + bR_2) \end{bmatrix}$$
 (16.2)

or the a, b scalars:

$$\frac{\partial(l)}{\partial a} = R_2$$

$$\frac{\partial(l)}{\partial b} = -R_1$$

Transforming a 3D line (R,(a,b)) from a world coordinate frame to a camera frame  $(R_w^c,t^w)$  is done by

$$R' = R_w^c R$$
$$a' = a - R_1^T t^w$$
$$b' = b - R_2^T t^w$$

Again, we need to redo the derivatives, as R is incremented from the right. The first argument is incremented from the left, but the result is incremented on the right:

$$R'(I + \Omega') = (AB)(I + \Omega') = (I + [S\omega]_{\times})AB$$

$$I + \Omega' = (AB)^{T}(I + [S\omega]_{\times})(AB)$$

$$\Omega' = R'^{T}[S\omega]_{\times}R'$$

$$\Omega' = [R'^{T}S\omega]_{\times}$$

$$\omega' = R'^{T}S\omega$$

For the second argument *R* we now simply have:

$$AB(I + \Omega') = AB(I + \Omega)$$

$$\Omega' = \Omega$$

$$\omega' = \omega$$

The scalar derivatives can be found by realizing that

$$\begin{pmatrix} a' \\ b' \\ \dots \end{pmatrix} = \begin{pmatrix} a \\ b \\ 0 \end{pmatrix} - R^T t^w$$

where we don't care about the third row. Hence

$$\frac{\partial ((R(I+\Omega_2))^T t^w)}{\partial \omega} = -\frac{\partial (\Omega_2 R^T t^w)}{\partial \omega} = -[R^T t^w]_{\times} = \begin{bmatrix} 0 & R_3^T t^w & -R_2^T t^w \\ -R_3^T t^w & 0 & R_1^T t^w \\ \dots & \dots & 0 \end{bmatrix}$$

# 17 Aligning 3D Scans

Below is the explanaition underlying Pose3.align, i.e. aligning two point clouds using SVD. Inspired but modified from CVOnline...

Our model is

$$p^{c} = R(p^{w} - t)$$

i.e., R is from camera to world, and t is the camera location in world coordinates. The objective function is

$$\frac{1}{2}\sum (p^{c} - R(p^{w} - t))^{2} = \frac{1}{2}\sum (p^{c} - Rp^{w} + Rt)^{2} = \frac{1}{2}\sum (p^{c} - Rp^{w} - t')^{2}$$
(17.1)

where t' = -Rt is the location of the origin in the camera frame. Taking the derivative with respect to t' and setting to zero we have

$$\sum \left( p^c - Rp^w - t' \right) = 0$$

or

$$t' = \frac{1}{n} \sum_{c} (p^{c} - Rp^{w}) = \bar{p}^{c} - R\bar{p}^{w}$$
 (17.2)

here  $\bar{p}^c$  and  $\bar{p}^w$  are the point cloud centroids. Substituting back into (17.1), we get

$$\frac{1}{2}\sum (p^c - R(p^w - t))^2 = \frac{1}{2}\sum ((p^c - \bar{p}^c) - R(p^w - \bar{p}^w))^2 = \frac{1}{2}\sum (\hat{p}^c - R\hat{p}^w)^2$$

Now, to minimize the above it suffices to maximize (see CVOnline)

$$trace(R^TC)$$

where  $C = \sum \hat{p}^c (\hat{p}^w)^T$  is the correlation matrix. Intuitively, the cloud of points is rotated to align with the principal axes. This can be achieved by SVD decomposition on C

$$C = USV^T$$

and setting

$$R = UV^T$$

Clearly, from (17.2) we then also recover the optimal t as

$$t = \bar{p}^w - R^T \bar{p}^c$$

# **Appendix**

#### **Differentiation Rules**

Spivak [4] also notes some multivariate derivative rules defined component-wise, but they are not that useful in practice:

• Since  $f: \mathbb{R}^n \to \mathbb{R}^m$  is defined in terms of m component functions  $f^i$ , then f is differentiable at a iff each  $f^i$  is, and the Jacobian matrix  $F_a$  is the  $m \times n$  matrix whose  $i^{th}$  row is  $(f^i)'(a)$ :

$$F_a \stackrel{\Delta}{=} f'(a) = \left[ \begin{array}{c} \left(f^1\right)'(a) \\ \vdots \\ \left(f^m\right)'(a) \end{array} \right]$$

• Scalar differentiation rules: if  $f,g:\mathbb{R}^n\to\mathbb{R}$  are differentiable at a, then

$$(f+g)'(a) = F_a + G_a$$
  
 $(f \cdot g)'(a) = g(a)F_a + f(a)G_a$   
 $(f/g)'(a) = \frac{1}{g(a)^2} [g(a)F_a - f(a)G_a]$ 

#### **Tangent Spaces and the Tangent Bundle**

The following is adapted from Appendix A in [3].

The **tangent space**  $T_pM$  of a manifold M at a point  $p \in M$  is the vector space of **tangent vectors** at p. The **tangent bundle** TM is the set of all tangent vectors

$$TM \stackrel{\Delta}{=} \bigcup_{p \in M} T_p M$$

A vector field  $X: M \to TM$  assigns a single tangent vector  $x \in T_pM$  to each point p.

If  $F: M \to N$  is a smooth map from a manifold M to a manifold N, then we can define the **tangent map** of F at p as the linear map  $F_{*p}: T_pM \to T_{F(p)}N$  that maps tangent vectors in  $T_pM$  at p to tangent vectors in  $T_{F(p)}N$  at the image F(p).

# Homomorphisms

The following *might be* relevant [2, page 45]: suppose that  $\Phi: G \to H$  is a mapping (Lie group homomorphism). Then there exists a unique linear map  $\phi: \mathfrak{g} \to \mathfrak{h}$ 

$$\phi(\hat{x}) \stackrel{\Delta}{=} \lim_{t \to 0} \frac{d}{dt} \Phi\left(e^{t\hat{x}}\right)$$

such that

1. 
$$\Phi\left(e^{\hat{x}}\right) = e^{\phi(\hat{x})}$$

2. 
$$\phi(T\hat{x}T^{-1}) = \Phi(T)\phi(\hat{x})\Phi(T^{-1})$$

3. 
$$\phi([\hat{x}, \hat{y}]) = [\phi(\hat{x}), \phi(\hat{y})]$$

In other words, the map  $\phi$  is the derivative of  $\Phi$  at the identity. As an example, suppose  $\Phi(g) = g^{-1}$ , then the corresponding derivative *at the identity* is

$$\phi(\hat{x}) \stackrel{\Delta}{=} \lim_{t \to 0} \frac{d}{dt} \left( e^{t\hat{x}} \right)^{-1} = \lim_{t \to 0} \frac{d}{dt} e^{-t\hat{x}} = -\hat{x} \lim_{t \to 0} e^{-t\hat{x}} = -\hat{x}$$

In general it suffices to compute  $\phi$  for a basis of  $\mathfrak{g}$ .

# References

- [1] P.-A. Absil, R. Mahony, and R. Sepulchre. *Optimization Algorithms on Matrix Manifolds*. Princeton University Press, Princeton, NJ, USA, 2007.
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