Chapter 1

Calculation of rotation coefficient

When the metric g is globally flat with no additional constraints like boundary alignment, a globally integrable frame field is achievable by parallel transport. No singularities in the frame field would be present. However, this is not possible in general. In this section, by starting from the assumption that the metric is flat, we recover the rotation happening by parallel transport under the connection ω which allows us to pull back the covariant derivative based Dirichlet energy and minimize as if we were minimizing the Dirichlet energy in Euclidean coordinates.

The smoothness measure $\mathcal{D}R$ is zero if all frames are parallel to each other under the connection ω , i.e., if all frames are the same if parallel transported to the same point. This is deliberately kept vague as parallel transport is path dependent in general (parallel transport is path independent if the metric is flat). To get a feeling for the problem statement, see figure 1.1.

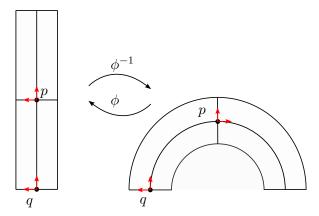


Figure 1.1. Under the metric induced by ϕ , the frame at q is parallel to p. To compare them, we need to recover how p is rotated under ω .

As we want parallelness under ω along a path γ , we set $\mathcal{D}R \stackrel{!}{=} 0$ and treat it as a set of differential equations. Again, as R essentially consists of three rotation fields, what is meant that $\mathcal{D}R_i = 0$ for each field.

Differential Equation Let p,q be points on the manifold and $\ell:[0,1]\to\mathcal{M}$ a path connecting them, with $\ell(0)=q$ and $\ell(1)=p$. Our differential equation is then given by

$$\mathbf{0} = dR_i(\ell(t)) + \omega(\ell(t))R_i(\ell(t)) \tag{1.1}$$

which we rearrange to

$$\underbrace{-\omega(\ell(t))}_{\mathbf{A}(t)}\underbrace{R_i(\ell(t))}_{\mathbf{\alpha}(t)} = \underbrace{dR_i(\ell(t))}_{\dot{\mathbf{\alpha}}(t)}$$
(1.2)

where we explicitly indicate that ω depends on the point evaluated and is not constant. Do not get confused what we are differentiating: The differential equation consists of mappings

$$\omega: \mathcal{M} \to \mathbb{R}^{3\times 3}$$
 and $R_i: \mathcal{M} \to \mathbb{R}^3$.

Thus, the concatenation with $\ell:[0,1]\to\mathcal{M}$ gives us mappings $\boldsymbol{A}:[0,1]\to\mathbb{R}^{3\times3}$ and $\boldsymbol{\alpha}:[0,1]\to\mathbb{R}^3$ where it makes sense to take the derivative with respect to t. This differential equation has the form of a matrix differential equation, for which a general closed form solution is hard to find. However, when ω and its integral $\int_0^t -\omega(\ell(s))ds$ commute, the general solution $\boldsymbol{\alpha}(t)=e^{\int_0^t \boldsymbol{A}(s)ds}\boldsymbol{\alpha}(0)$ exists, which is the case when ω along ℓ rotate around the same axis (the same way rotation matrices commute when they rotate around the same axis).

Let $R: \mathcal{M} \to SO(3)$ be a rotation field, i.e. R(p), R(q) are orthogonal frames. Under the initial condition that $R(p) = \mathrm{Id}$, the equation

$$R(q) = \exp(R_{pq}(\omega))R(p)$$

is a differential equation that corresponds to the parallel transport under the connection ω of the frame along ℓ . To recover this rotation R_{pq} , we integrate ω along ℓ .

Setup We parametrize the path by $\ell(0) = a, \ell(1) = b$. We resort to numerical integration for R_{ab} and cut the path into n small segments, i.e.

$$R_{ab} = R_n R_{n-1} \cdots R_1$$

where $R_i = \exp(-\omega(\dot{\ell}(i\gamma))\gamma) = \exp((\int W^\top dp)_\times)$, and γ is the length of a segment and $\dot{\ell}(s) = \frac{\partial \ell}{\partial s}(s)$. Calculating the exponential map of an antisymmetric matrix (which $\omega \in \mathfrak{so}(3)$ is) can be done with Rodrigues' formula:

$$\exp(u_{\times}) = \operatorname{Id} + \sin(\theta)\hat{u}_{\times} + (1 - \cos(\theta))\hat{u}_{\times}^{2}$$

where $\theta = ||u||_2$ is the rotation angle and $\hat{u} = u/\theta$ is the rotation axis. We use the trapezoidal rule to evaluate the a short interval of the integral of W, which is given by

$$R_{ab} = \exp\left(\left(\frac{1}{2}(W_a + W_b)^{\top}(b - a)\right)\right)$$

where W_a, W_b is solved for by the 9x9 linear system given by A_{\times} and $\nabla \times A$.

1.1 Piecewise linear discretization

We discretize our metric field with a tetrahedral mesh \mathcal{T} . At each vertex, we attach a metric and linearly interpolate with barycentric coordinates within a tet.

Let $A_i \in \mathbb{R}^{3x3}$, $i \in \{1, 2, 3, 4\}$ be the square root metrics at the vertices $v_i \in \mathbb{R}^3$ of a tet, such that $A_i^2 = g(v_i)$. We represent a tet given by its four vertices by a 3x4 matrix, i.e.

$$\begin{pmatrix} | & | & | & | \\ v_1 & v_2 & v_3 & v_4 \\ | & | & | & | \end{pmatrix} \in \mathbb{R}^{3 \times 4}.$$

Any point p within the tet can then be represented as

$$p = \alpha v_1 + \beta v_2 + \gamma v_3 + \delta v_4$$

with $\alpha, \beta, \gamma, \delta \ge 0$ and $\alpha + \beta + \gamma + \delta = 1$. This is a linear transformation between two coordinate systems, which we can write in matrix form as

$$\underbrace{\begin{pmatrix} \begin{vmatrix} & & & & & & \\ v_1 & v_2 & v_3 & v_4 \\ & & & & & \\ 1 & 1 & 1 & 1 \end{pmatrix}}_{T^{-1}} \underbrace{\begin{pmatrix} \alpha \\ \beta \\ \gamma \\ \delta \end{pmatrix}}_{\lambda} = \underbrace{\begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}}_{p} \iff T^{-1}\lambda = p \iff \lambda = Tp$$

T always exists because v_1, \ldots, v_4 are linearly independent, else it would not be a tetrahedron. By denoting $T = \{t_{ij}\}_{i,j \in \{1,\ldots,4\}}$, we can write our barycentric functions as

$$\alpha(x, y, z) = t_{11}x + t_{12}y + t_{13}z + t_{14}$$

$$\beta(x, y, z) = t_{21}x + t_{22}y + t_{23}z + t_{24}$$

$$\gamma(x, y, z) = t_{31}x + t_{32}y + t_{33}z + t_{34}$$

$$\delta(x, y, z) = t_{41}x + t_{42}y + t_{43}z + t_{44}$$

The convex combination

$$A(x, y, z) = \alpha A_1 + \beta A_2 + \gamma A_3 + \delta A_4$$

is the metric prescribed in the tet. To find $\nabla \times A$, let $A = (A^1, A^2, A^3)$. We will need the derivatives for the curl, so let

$$(A_j^i)_x \triangleq \frac{\partial A_j^i}{\partial x}$$

be the derivative with respect to x of entry i, j. E.g. $(A_i^i)_x$ is given by

$$(A_j^i)_x = \alpha_x (A_1)_j^i + \beta_x (A_2)_j^i + \gamma_x (A_3)_j^i + \delta_x (A_4)_j^i = t_{11} (A_1)_j^i + t_{21} (A_2)_j^i + t_{31} (A_3)_j^i + t_{41} (A_4)_j^i$$

If we write $T=(T^1,T^2,T^3,T^4)$ and collect $(A_k)^i_j$ into a vector

$$\bar{A}_{j}^{i} = \begin{pmatrix} (A_{1})_{j}^{i} \\ (A_{2})_{j}^{i} \\ (A_{3})_{j}^{i} \\ (A_{4})_{j}^{i} \end{pmatrix}$$

this can be shortened to $\bar{A}_j^{i}^{\top} T^1 = (A_j^i)_x$. Analogously, we get

$$(A_i^i)_y = \bar{A_i^i}^\top T^2$$
 and $(A_i^i)_z = \bar{A_i^i}^\top T^3$

The curl is then given by

$$\nabla \times A^{i} = \begin{pmatrix} (A_{3}^{i})_{y} - (A_{2}^{i})_{z} \\ (A_{1}^{i})_{z} - (A_{3}^{i})_{x} \\ (A_{2}^{i})_{x} - (A_{1}^{i})_{y} \end{pmatrix} = \begin{pmatrix} \bar{A}_{3}^{i} & T^{2} - \bar{A}_{2}^{i} & T^{3} \\ \bar{A}_{3}^{i} & T^{3} - \bar{A}_{3}^{i} & T^{1} \\ \bar{A}_{2}^{i} & T^{3} - \bar{A}_{1}^{i} & T^{2} \end{pmatrix}$$

and $\nabla \times A = \nabla \times (A^1, A^2, A^3)$. Notice that the curl is constant within a tetrahedron.

1.2 Recursive subdivision

Whenever the rotation coefficient R_{pq} is needed between some points p and q, it is unclear ahead of time how many sampling points on the line ℓ are needed such that R_{pq} accurately describes how the frame rotates along ℓ . We apply a recursive subdivision scheme to recursively sample more points on ℓ only

where is needed until sampling more points leads to no noticable improvement anymore (see figure 1.2). We begin by calculating R_{ab} with just the endpoints. This coefficient is then compared to the result if the midpoint was sampled as well, so i.e. if

$$\frac{||R_{ab} - R_{am} \cdot R_{mb}||_2^2}{\ell^2} < \varepsilon$$

then no measurable improvement happened. We divide by the length of the segment \vec{ab} , because the segments get smaller and we want the tolerance ε to remain the same. This approach has the advantage of only sampling points where there is improvement. See section ?? for results.

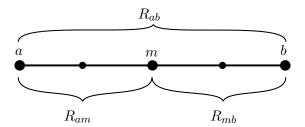


Figure 1.2. Points are recursively sampled as midpoints between the line \vec{ab} . If sampling more points within some line segment leads to noticable improvement, more points are sampled.

The following code does what is described above.

Algorithm 1 Recursive Subdivision

```
1: recursiveDivide (a, b)

2: R_1 = Rotation(a,b)

3: \ell = length(a - b)

4: midpoint = \frac{a+b}{2}

5: if \frac{||R_1 - Rotation(a, midpoint) \cdot Rotation(midpoint, b)||_2^2}{\ell^2} < \varepsilon

6: return R_1

7: else

8: return recursiveDivide(a, midpoint) \cdot recursiveDivide(midpoint, b)
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