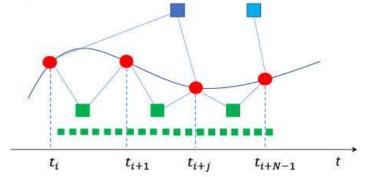
☐ Continuous-time optimization via B-spline interpolation:

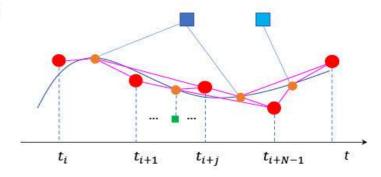
KEY TAKEOUT:

A pose \mathbf{T}_t at time $t \in [t_i, t_{i+1})$ can be linearly interpolated from N control points $\mathbf{T}_i, \mathbf{T}_{i+1}, \dots \mathbf{T}_{i+N-1}$ via some time dependent weights.

ADVANTAGES:

- Can integrate arbitrary number of sensors (multiple IMUs, multiple monocular VIOs...)
- Can estimate time delay.
- Can directly compensate for motion distortion in the MAP optimization.





- Continuous-time optimization via B-spline interpolation:
 - B-spline is defined by:
 - Its order N (or degree N-1), knot length Δt ,
 - $K \ge N$ knots (also called control points):

$$\{\mathbf{T}_i \triangleq (\mathbf{R}_i, \mathbf{p}_i)\}_{i=0}^{K-1}, \mathbf{R}_i \in SO3, \mathbf{p}_i \in \mathbb{R}^3$$

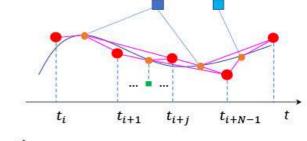
$$(s(t)) = \mathbf{n}_i + \sum_{i=0}^{N-1} \lambda_i(s(t)) \mathbf{n}_{i+1} = \mathbf{n}_i + \sum_{i=0}^{N-1} \tilde{\lambda}_i(s(t)) (\mathbf{n}_{i+1} - \mathbf{n}_{i+1})$$

$$\mathbf{p}(s(t)) = \mathbf{p}_i + \sum_{j=1}^{N-1} \lambda_j(s(t)) \, \mathbf{p}_{i+j} = \mathbf{p}_i + \sum_{j=1}^{N-1} \tilde{\lambda}_j(s(t)) \, (\mathbf{p}_{i+j} - \mathbf{p}_{i+j-1})$$

$$\mathbf{R}(s(t)) = \mathbf{R}_i \prod_{j=1}^{N-1} \mathrm{Exp}\left(\tilde{\lambda}_j(s(t)) \operatorname{Log}(\mathbf{q}_{i+j-1}^{-1} \circ \mathbf{q}_{i+j})\right) = \mathbf{R}_i \prod_{j=1}^{N-1} A_j$$

$$\underbrace{(1,\lambda_1,\lambda_2,\ldots,\lambda_{N-1})}_{N\times 1} \triangleq \lambda(s) = \underbrace{\mathbf{B}(N)(1,s,s^2,\ldots,s^{N-1})}_{N\times N}$$

$$\underbrace{\begin{pmatrix} 1, \tilde{\lambda}_1, \tilde{\lambda}_2, \dots, \tilde{\lambda}_{N-1} \end{pmatrix}}_{N \times 1} \triangleq \lambda(s) = \underbrace{\widetilde{\mathbf{B}}(N)(1, s, s^2, \dots, s^{N-1})}_{N \times N} \qquad s \triangleq \underbrace{\frac{(t - t_i)}{\Delta t}}_{\Delta t}, \forall t \in [t_i, t_{i+1}),$$



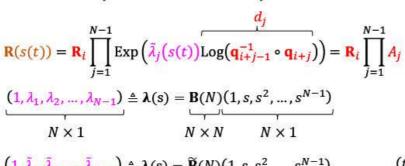
$$s \triangleq \frac{(t-t_i)}{\Delta t}, \forall t \in [t_i, t_{i+1}),$$

- ☐ Continuous-time optimization via B-spline interpolation:
 - B-spline is defined by:
 - Its order N (or degree N-1), knot length Δt ,
 - $K \ge N$ knots (also called control points):

$$\begin{aligned} \{\mathbf{T}_i \triangleq (\mathbf{R}_i, \mathbf{p}_i)\}_{i=0}^{K-1}, \, \mathbf{R}_i \in \text{SO3}, \, \mathbf{p}_i \in \mathbb{R}^3 \\ \mathbf{p}(s(t)) = \mathbf{p}_i + \sum_{i=1}^{N-1} \lambda_j(s(t)) \, \mathbf{p}_{i+j} = \mathbf{p}_i + \sum_{i=1}^{N-1} \tilde{\lambda}_j(s(t)) \, \left(\mathbf{p}_{i+j} - \mathbf{p}_{i+j-1}\right) \end{aligned}$$

KEY TAKEOUT:

A pose \mathbf{T}_t at time $t \in [t_i, t_{i+1})$ can be linearly interpolated from N control points $\mathbf{T}_i, \mathbf{T}_{i+1}, ... \mathbf{T}_{i+N-1}$ via some time dependent weights.



$$t_i$$
 t_{i+1} t_{i+j} t_{i+N-1} t

$$\underbrace{\begin{pmatrix} 1, \tilde{\lambda}_1, \tilde{\lambda}_2, \dots, \tilde{\lambda}_{N-1} \end{pmatrix}}_{N \times 1} \triangleq \lambda(s) = \underbrace{\tilde{\mathbf{B}}(N)(1, s, s^2, \dots, s^{N-1})}_{N \times N} \qquad s \triangleq \underbrace{(t - t_i)}_{\Delta t}, \forall t \in [t_i, t_{i+1}),$$

☐ Gauss-Newton B-SPLINE Optimization on Manifold:

Need to calculate the gradient \rightarrow Jacobian.

Calculated as in Discrete Time case

For 1st order observations, the Jacobian is:

$$J_{\mathbf{T}_{j}}^{Z} = \frac{\partial h(\mathbf{T}_{t}, \check{Z})}{\partial \mathbf{T}_{j}} = \frac{\partial h(\mathbf{T}_{t}, \check{Z})}{\partial \mathbf{T}_{t}} \frac{\partial \mathbf{T}_{t}}{\partial \mathbf{T}_{j}}$$

■ KEY TAKEOUT:

Calculate the Jacobian as normal, then multiple it with $\frac{\partial \mathbf{T}_t}{\partial \mathbf{T}_t}$

$$\frac{\partial \mathbf{p}_t}{\partial \mathbf{p}_j} = \lambda_j$$

$$\frac{\partial \mathbf{R}_{t}}{\partial \mathbf{R}_{j}} = \tilde{\lambda}_{j} \left(\prod_{j+1}^{m=N-1} \mathbf{A}_{m}^{\mathsf{T}} \right) J_{r} \left(\tilde{\lambda}_{j} \mathbf{d}_{j} \right) J_{r}^{-1} \left(\mathbf{d}_{j} \right) - \tilde{\lambda}_{j+1} \left(\prod_{j+2}^{m=N-1} \mathbf{A}_{m}^{\mathsf{T}} \right) J_{r} \left(\tilde{\lambda}_{j+1} \mathbf{d}_{j+1} \right) J_{r}^{-1} \left(-\mathbf{d}_{j+1} \right)$$

Previous slide

☐ Gauss-Newton B-SPLINE Optimization on Manifold:

Acceleration factor:

$$J_{\mathbf{R}_{j}}^{a} = \frac{\partial}{\partial \mathbf{R}_{j}} \left[\mathbf{R}_{t}^{-1} (\ddot{\boldsymbol{p}}_{t} + \mathbf{g}) - \breve{a} \right] = \left[\mathbf{R}_{t}^{-1} \ddot{\boldsymbol{p}}_{t} \right]_{\times} \boxed{\frac{\partial \mathbf{R}_{t}}{\partial \mathbf{R}_{j}}}$$

$$J_{\mathbf{p}_{j}}^{a} = \frac{\partial}{\partial \mathbf{p}_{j}} [\mathbf{R}_{t}^{-1} (\ddot{\mathbf{p}}_{t} + \mathbf{g}) - \breve{a}] = \mathbf{R}_{t}^{-1} \boxed{\frac{\partial \ddot{\mathbf{p}}_{t}}{\partial \mathbf{p}_{j}}}$$

$$\frac{\partial \ddot{\mathbf{p}}_t}{\partial \mathbf{p}_j} = \ddot{\lambda}_j = \frac{\lambda_j}{\Delta t^2} \frac{ds^j}{ds^2}$$

☐ Gauss-Newton B-SPLINE Optimization on Manifold:

Special factor based on IMU:

$$J_{\mathbf{R}_{j}}^{\omega} = \frac{\partial}{\partial \mathbf{R}_{i}} (\boldsymbol{\omega}_{t} - \boldsymbol{\omega}) = \frac{\partial \boldsymbol{\omega}_{t}}{\partial \mathbf{R}_{i}},$$

$$\omega_t = \omega^{(N)}$$
,

$$\omega^{(j)} = A_{j-1}^{\mathsf{T}} \omega^{(j-1)} + \dot{\tilde{\lambda}}_{j-1} d_{j-1}$$

$$\frac{\partial \omega_t}{\partial \mathbf{R}_j} = \frac{\partial \omega^{(j)}}{\partial \mathbf{d}_j} J_r^{-1} \left(\frac{\mathbf{d}_j}{\mathbf{d}_j} \right) - \frac{\partial \omega^{(j+1)}}{\partial \mathbf{d}_{j+1}} J_r^{-1} \left(-\frac{\mathbf{d}_{j+1}}{\mathbf{d}_{j+1}} \right)$$

$$\frac{\partial \omega^{(j)}}{\partial \mathbf{d}_{j}} = \left(\prod_{j+1}^{m=N-1} A_{m}^{\mathsf{T}} \right) \left(\tilde{\lambda}_{j} A_{j}^{\mathsf{T}} \left[\omega^{(j)} \right]_{\mathsf{X}} J_{r} \left(-\tilde{\lambda}_{j} d_{j} \right) + \dot{\tilde{\lambda}}_{j} I \right)$$

- ☐ Verified with Ceres Automatic derivatives
 - Exactly the same as automatic derivatives.
 - 80% faster
 - More concise and clearly written code © .

```
Analytic Jacobian: Size 12 42. Params: 14. Cost: 97.901162. Time: 1.064472.
-0.0212424 -0.006386221 -0.6162263 -0.221867 0.308899 -0.0741156
-0.0652404 -0.018993 -0.6053849 -0.322417 -0.163202 -0.153942
-0.00488883 -0.006627768 -0.0198866 0.168155 0.0555763 -0.3822
-0.00488883 -0.00173455 -0.6575933 1.20734 0.103925 -3.29583
-0.165354 0.0173455 -0.6575933 1.20734 0.103925 -3.29583
-0.165354 0.0173455 -0.6575933 1.20734 0.103925 -3.29583
-0.0212424 -0.606336221 -0.6102263 -0.221867 0.30999 -0.0741156
-0.0012424 -0.606336221 -0.6102263 -0.221867 0.30999 -0.0741156
-0.0012424 -0.606336231 -0.6053849 -0.322187 -0.635202 -0.153942
-0.0012424 -0.606336231 -0.6053849 -0.3221867 0.30999 -0.0741156
-0.0012424 -0.606336235 -0.6053849 -0.3221867 0.30999 -0.6153942
-0.00129327 -0.00173455 -0.6575933 1.20734 0.103925 -0.153942
-0.0048883 -0.60662768 -0.6198866 0.168155 0.0555763 -0.3822
-0.00173455 -0.6575933 1.20734 0.103925 -3.29583
-0.065558 -0.00173455 -0.6575933 1.20734 0.103925 -3.29583
-0.165524 0.0711059 0.054218 7.18386 -3.61627 1.55767

TNU Jacobian PASSED! Time reduced: 83.95 %

Pose Analytic Jacobian: Size 6 42. Params: 12. Cost: 1.310115, Time: 0.770401.
-0.00942791 0.00213804 0.00468003 0.174813 -0.157822 0.0714925
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
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-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0013691 0.00213064 0.00468003 0.174813 -0.157822 0.0714925
-0.0029327 0.006677144 0.00817702 -0.0889921 -0.0127591 0.241422
-0.0013691 0.00213064 0.00468088 0.4619 0.999523 -1.08712
-0.0013691 0.00520877 0.0108888 0.4619 0.999523 -1.08712
-0.0013691 0.00520877 0.006678888 0.4619 0.999523 -1.08712
-0.0013691 0.00520877 0.00667888 0.00520888 0.0052085
```