B-Splines for Robotic Applications

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Abstract

These notes provide an overview of b-splines and their applications to robotics. In particular, we have in mind applications to path planning for aerial vehicles, model predictive control, and fixed-lag state estimation.

1 Motivation

The objective of these notes is to explore spline methods for robotic applications. In general, the position of a robot in Euclidian space can be described by a time parametrized trajectory $\mathbf{p}(t) \in \mathbb{R}^3$, $t \in [a, b]$. The time parametrized trajectory can be parameterized using a weighted sum of basic function as

$$\mathbf{p}(t) = \sum_{j=0}^{n-1} \mathbf{c}_j \phi_j(t),$$

where $\mathbf{c}_j \in \mathbb{R}^3$, and $\phi_j(t)$ are a set of basis functions. For example, the basis functions could be the set of polynomial power function $\phi_j(t) = t^j/j!$, or the set of sinusoidal function $\phi_j(t) = \sin(\frac{2\pi j}{n}t)$. The disadvantage of both the polynomial power functions and sinusoidal functions is that the basis functions are defined for all $t \in [a, b]$ and so each control points j influences the entire trajectory. Another disadvantage is that a large number of basis functions may be required to represent complicated trajectories.

In these notes, we will use b-spline basis functions which have a number of very nice properties that we will explore. In particular, a *b-spline* trajectory has the following form

$$\mathbf{p}(t) = \sum_{j=0}^{n} \mathbf{c}_{j} B_{j}^{k}(t; \mathbf{t}),$$

where $\mathbf{c}_j \in \mathbb{R}^3$ are the control points, $\mathbf{t} = (\tau_0, \tau_1, \tau_2, \dots, \tau_T)$ are called the knot points where $i < j \implies \tau_i \le \tau_j$, and $B_j^k(t; \mathbf{t})$ are the b-spline basis functions of order k. The spline trajectories will be defined for t in the span of the knot points, i.e., $t \in [\tau_0, \tau_T]$.

Section 2 defines the b-spline basis function $B_j^k(t;\mathbf{t})$ and describes some of their properties that will be useful for path planning.

2 B-Spline Basis Functions

The B-spline basis function are defined by the following recursive formula:

$$B_{j}^{0}(t;\mathbf{t}) = \begin{cases} 1 & \text{if } \tau_{j} \leq t \leq \tau_{j+1} \\ 0 & \text{otherwise} \end{cases}$$

$$B_{j}^{k}(t;\mathbf{t}) = \frac{t - \tau_{j}}{\tau_{j+k} - \tau_{j}} B_{j}^{k-1}(t;\mathbf{t}) + \frac{\tau_{j+k+1} - t}{\tau_{j+k+1} - \tau_{j+1}} B_{j+1}^{k-1}(t;\mathbf{t}).$$

2.1 Zeroth order basis

If the knot vector is given by

$$\mathbf{t} = [\tau_0, \tau_1, \tau_2] \stackrel{\triangle}{=} [0, 1, 2],$$

then there are two basis function of order k=0 given by

$$B_0^0(t; \mathbf{t}) = \begin{cases} 1 & \text{if } \tau_0 \le t \le \tau_1 \\ 0 & \text{otherwise} \end{cases}$$
$$B_1^0(t; \mathbf{t}) = \begin{cases} 1 & \text{if } \tau_1 \le t \le \tau_2 \\ 0 & \text{otherwise} \end{cases}$$

where $B_0^0(t)$ and $B_0^0(t)$ are shown in Figure 1. Additional zeroth order basis

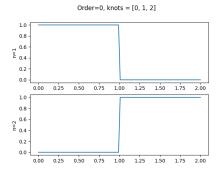


Figure 1: Zeroth order spline basis

function can be defined by expanding the knot vector.

2.2 First order basis

If the knot vector is given by

$$\mathbf{t} = [\tau_0, \tau_1, \tau_2, \tau_3, \tau_4] \stackrel{\triangle}{=} [0, 0, 1, 2, 2],$$

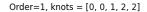
then there are two basis function of order k=1 given by

$$B_0^0(t; \mathbf{t}) = \frac{t - \tau_0}{\tau_1 - \tau_0} B_0^0(t; \mathbf{t}) + \frac{\tau_2 - t}{\tau_2 - \tau_1} B_1^0(t; \mathbf{t}) = \begin{cases} 1 - t & \text{if } 0 \le t \le 1\\ 0 & \text{otherwise} \end{cases}$$

$$B_1^1(t; \mathbf{t}) = \frac{t - \tau_1}{\tau_2 - \tau_1} B_1^0(t; \mathbf{t}) + \frac{\tau_3 - t}{\tau_3 - \tau_2} B_2^0(t; \mathbf{t}) = \begin{cases} t & \text{if } 0 \le t \le 1\\ 2 - t & 1 \le t \le 2\\ 0 & \text{otherwise} \end{cases}$$

$$B_2^1(t; \mathbf{t}) = \frac{t - \tau_2}{\tau_3 - \tau_2} B_2^0(t; \mathbf{t}) + \frac{\tau_4 - t}{\tau_4 - \tau_3} B_3^0(t; \mathbf{t}) = \begin{cases} t - 1 & \text{if } 1 \le t \le 2\\ 0 & \text{otherwise} \end{cases}$$

where $B_0^1(t;\mathbf{t}),\,B_1^1(t;\mathbf{t}),\,$ and $B_2^1(t;\mathbf{t})$ are shown in Figure 2. Expanding the knot



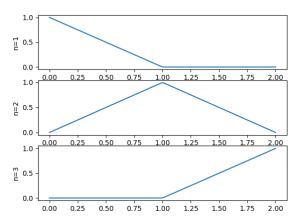


Figure 2: First order spline basis

vector to

$$\mathbf{t}' = [\tau_0, \tau_1, \tau_2, \tau_3, \tau_4, \tau_5] \stackrel{\triangle}{=} [0, 0, 1, 2, 3, 3],$$

results in $B_2^1(t;\mathbf{t}')$ looking like $B_1^1(t;\mathbf{t})$ shifted to the right by one, and $B_3^1(t;\mathbf{t}')$ looking like $B_2^1(t;\mathbf{t})$ shifted to the right by one.

2.3 Second order basis

Order=2, knots = [0, 0, 0, 1, 2, 3, 3, 3]

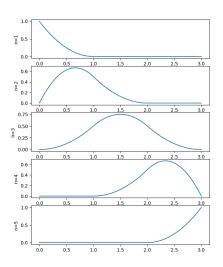


Figure 3: Second order spline basis

2.4 Third order basis

2.5 Eigth order basis

2.6 Derivative of basis functions

The general formula for the derivative of the basis functions is [?]

$$\frac{d^m}{dt^m}B_j^k(t;\mathbf{t}) = k\left(\frac{\frac{d^{m-1}}{dt^{m-1}}B_j^{k-1}(t;\mathbf{t})}{t_{j+k}-t_j} - \frac{\frac{d^{m-1}}{dt^{m-1}}B_{j+1}^{k-1}(t;\mathbf{t})}{t_{j+k+1}-t_{j+1}}\right).$$

3 B-Spline Trajectories

If the k^{th} -order B-spline curve with knot vector

$$\mathbf{t} = \boldsymbol{\tau} = (\tau_0, \tau_1, \dots, \tau_K)$$

is given by

$$\mathbf{C}(t) = \sum_{j=0}^{n} B_j^k(t; \mathbf{t}) \mathbf{c}_j,$$

where $\{\mathbf{c}_j\}_{j=0}^n$ are called the control points.

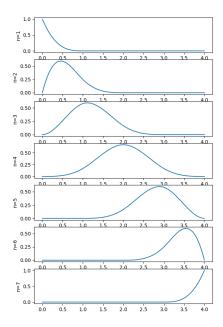


Figure 4: Third order spline basis

For path planning we will construct paths between the initial time t_0 and the final time $t_f > t_0$. We will divide the time interval into n equal segments, and we will always use a knot vector of length

$$K = k + (n+1) + k$$

where $n \geq m + 1$, and where

$$k_{j} = \begin{cases} t_{0}, & 0 \leq j \leq m \\ t_{0} + \frac{(j-m)(t_{f}-t_{0})}{n}, & m+1 \leq j \leq m+n-1 \\ t_{f}, & m+n \leq j \leq 2m+n+1 \end{cases}$$

or

$$\mathbf{t}_m = (\underbrace{t_0, t_0, \dots, t_0}_{m+1}, t_0 + \Delta, t_0 + 2\Delta, \dots, t_0 + (n-1)\Delta, \underbrace{t_f, t_f, \dots, t_f}_{m+1}),$$

where n is the number of control points, and $\Delta = (t_f - t_0)/n$. Knot vectors of this form are said to be *uniform* knot vectors.

Order=8, knots = [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 9, 9, 9, 9, 9, 9, 9, 9]

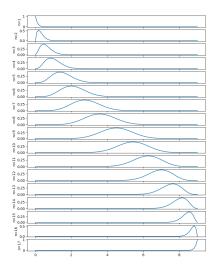


Figure 5: Eigth order spline basis

In the rest of these notes, we will use the shorthand notation

$$B_j^m(t) \equiv B_j^m(t; \mathbf{t}_m).$$

The knot vector \mathbf{t}_m has K=2m+n+1 elements. A b-spline with knots \mathbf{t}_m requires a total of N=n+m control points, where one control point is needed for each interval for a total of n control points, and the extra m control points are required to allow the extra degrees of freedom.

3.1 SciPy BSpline library

The SciPy library has a spline library.

The following commands will create a cubic spline.

```
import numpy as np from scipy.interpolate import BSpline
```

```
# initial and final time t0 = 0 tf = 5 order = 3 knots = np.array([t0, t0, t0, t0, (tf-t0)/3, 2*(tf-t0)/4, tf, tf, tf, tf])
```

```
\# num control > num knots - order - 1
     \operatorname{ctrl_pts} = \operatorname{np.array}([[0, 0, 0],
                               [0, 1, 0],
                              \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 \end{bmatrix},
                               [1, 1, 1]
    spl = BSpline(t=knots, c=ctrl_pts, k=order)
     plotSpline(spl)
   Where plotSpline is given below.
from math import ceil
from scipy.interpolate import BSpline
import matplotlib.pyplot as plt
def plotSpline(spl):
    t0 \, = \, spl.\,t\,[\,0\,] \quad \# \ first \ knot \ is \ t0
    tf = spl.t[-1] # last knot is tf
    # number of points in time vector so spacing is 0.01
    N = ceil((tf - t0)/0.01)
    t = np.linspace(t0, tf, N) # time vector
     position = spl(t)
    # 3D trajectory plot
    fig = plt.figure(1)
    ax = fig.add_subplot(111, projection='3d')
    # plot control points (convert YX(-Z) \rightarrow NED)
    ax.plot(spl.c[:, 1], spl.c[:, 0], -spl.c[:, 2],
               '-o', label='control points')
    # plot spline (convert YX(-Z) \rightarrow NED)
    ax.plot(position[:, 1], position[:, 0], -position[:, 2],
               'b', label='spline')
    ax.legend()
    ax.set_xlabel('x', fontsize=16, rotation=0)
    ax.set_ylabel('y', fontsize=16, rotation=0)
ax.set_zlabel('z', fontsize=16, rotation=0)
    \#ax.set_xlim3d([-10, 10])
     plt.show()
```

The resulting spline is shown in Figure 6.

3.2 Derivatives of b-splines

The k^{th} derivative of a b-spline is given by

$$\frac{d^k}{dt^k}\mathbf{C}(t) = \sum_{j=0}^n \left(\frac{d^k}{dt^k}B_j^m(t)\right)\mathbf{c}_i,$$

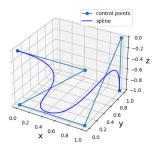


Figure 6: Example spline curve

Fact: If we let

$$\mathbf{d}_j = m \frac{\mathbf{c}_{j+1} - \mathbf{c}_j}{k_{j+m+1} - k_{j+1}},$$

then

$$\frac{d}{dt}\mathbf{C}(t) = \sum_{j=0}^{n-1} B_j^m(t)\mathbf{d}_j.$$

Given the knot vector \mathbf{t}_m , and suppose that we want to set the velocity vectors at the initial and final time, what is the constraint on the second and second-to-last control points? From the formula above

$$\mathbf{d}_0 = m \frac{\mathbf{c}_1 - \mathbf{c}_0}{k_{m+1} - k_1} = \mathbf{v}_0$$

implies that

$$\mathbf{c}_1 = \mathbf{c}_0 + \left(\frac{k_{m+1} - k_1}{m}\right) \mathbf{v}_0.$$

Similarly,

$$\mathbf{d}_{n-1} = m \frac{\mathbf{c}_n - \mathbf{c}_{n-1}}{k_{n+m} - k_n} = \mathbf{v}_f$$

implies that

$$\mathbf{c}_{n-1} = \mathbf{c}_n - \left(\frac{k_{n+m} - k_n}{m}\right) \mathbf{v}_f.$$

- 4 B-Spline Planning for Chains of Integrators
- 5 B-Splines on Lie Groups
- 6 Conclusions

References