# Ch3: Minimum-Time Trajectory Generation

Amin Fakhari, Spring 2024



# **Time-Optimal Time Scaling**



## Path, Time Scaling, and Trajectory

Path C(s) is a purely geometric description of the sequence of configurations achieved by the robot:  $C: [0,1] \to \mathbb{C}$ 

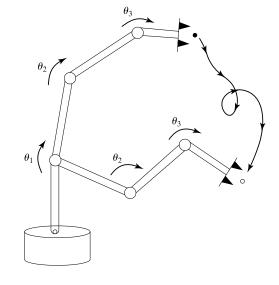
 $s \in [0,1]$ : scalar path parameter (0 at the start and 1 at the end of the path)

Robot's C-space

• As s increases from 0 to 1, the robot moves along the path.

Time Scaling s(t) specifies the times when those robot configurations are reached:

$$s: [0, t_f] \rightarrow [0,1]$$



**Trajectory** C(s(t)) or C(t) specifies the robot configuration as a function of time, i.e., the combination of a path and a time scaling.



#### Some Examples of Path Planning C(s), $s \in [0,1]$

• Point-to-Point Straight-Line Path in Joint Space:

$$\boldsymbol{\theta}(s) = \boldsymbol{\theta}_{\text{start}} + s(\boldsymbol{\theta}_{\text{end}} - \boldsymbol{\theta}_{\text{start}})$$

$$\boldsymbol{\theta} \in \mathbb{R}^n$$

• Point-to-Point Straight-Line Path in Task Space (in Cartesian Space  $\mathbb{R}^3$ ):

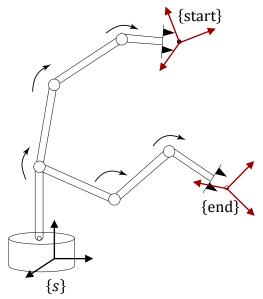
$$x(s) = x_{\text{start}} + s(x_{\text{end}} - x_{\text{start}})$$
  $x \in \mathbb{R}^m$ : minimum set of coordinates

$$p(s) = p_{\text{start}} + s(p_{\text{end}} - p_{\text{start}})$$
  $p \in \mathbb{R}^3$ ,  $R \in SO(3)$ 

$$R(s) = R_{\text{start}} \exp\left(\log\left(\underbrace{R_{\text{start}}^{\text{T}}R_{\text{end}}}_{R_{\text{start,end}}}\right)s\right)$$

• Point-to-Point Straight-Line Path in Task Space (in SE(3)):

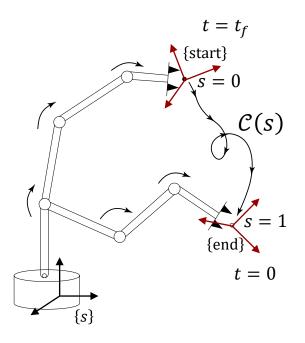
$$T(s) = T_{\text{start}} \exp(\log(\underbrace{T_{\text{start}}^{-1} T_{\text{end}}}_{T_{\text{start,end}}}) s)$$
  $T = (R, p) \in SE(3)$ 



#### **Time-Optimal Time Scaling**

Consider a case where the **path** C(s),  $s \in [0,1]$ , is fully specified by the task or an obstacle-avoiding path planner. The **time-optimal time scaling** is finding a **time scaling** s(t) that minimizes the time of motion along the path, subject to the robot's **actuator limits**.

A time-optimal trajectory maximizes the robot's productivity.





#### Actuation Constraints as a Function of S

In practice, the robot dynamics and joint actuator limits dependent on  $(\theta, \dot{\theta})$ , thus, the maximum available velocities and accelerations change along the path.

$$\boldsymbol{\tau} = \boldsymbol{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \dot{\boldsymbol{\theta}}^{\mathrm{T}}\boldsymbol{\Gamma}(\boldsymbol{\theta})\dot{\boldsymbol{\theta}} + \boldsymbol{g}(\boldsymbol{\theta}) \tag{1}$$

$$\tau_{i}^{\mathrm{min}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) \leq \tau_{i} \leq \tau_{i}^{\mathrm{max}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) \qquad i = 1, ..., n \qquad \text{(actuation constraints)} \tag{2}$$

A path C(s) can be always expressed in joint space  $\theta(s) \in \mathbb{R}^n$  using inverse kinematics. Thus,

$$\dot{\boldsymbol{\theta}} = \frac{d\boldsymbol{\theta}}{ds}\dot{s}, \quad \ddot{\boldsymbol{\theta}} = \frac{d\boldsymbol{\theta}}{ds}\ddot{s} + \frac{d^2\boldsymbol{\theta}}{ds^2}\dot{s}^2$$

Dynamics along the path:

(1) 
$$\rightarrow \tau = \underbrace{\left(M(\theta(s))\frac{d\theta}{ds}\right)}_{m(s)\in\mathbb{R}^n}\ddot{s} + \underbrace{\left(M(\theta(s))\frac{d^2\theta}{ds^2} + \left(\frac{d\theta}{ds}\right)^{\mathrm{T}}\Gamma(\theta(s))\frac{d\theta}{ds}\right)}_{c(s)\in\mathbb{R}^n}\dot{s}^2 + \underbrace{g(\theta(s))}_{g(s)\in\mathbb{R}^n}$$

$$= m(s)\ddot{s} + c(s)\dot{s}^2 + g(s) = m(s)\ddot{s} + h(s,\dot{s}) \qquad (3)$$



#### **Actuation Constraints as a Function of** S

(2) 
$$\rightarrow \tau_i^{\min}(s, \dot{s}) \le \tau_i \le \tau_i^{\max}(s, \dot{s})$$
 (4)

(3), (4) 
$$\rightarrow \tau_i^{\min}(s, \dot{s}) \le m_i(s) \ddot{s} + c_i(s) \dot{s}^2 + g_i(s) \le \tau_i^{\max}(s, \dot{s})$$
 (5)

Let define  $L_i(s, \dot{s})$  be the minimum  $\ddot{s}$  and  $U_i(s, \dot{s})$  be the maximum  $\ddot{s}$  satisfying (5):

$$\begin{aligned} L_i(s,\dot{s}) &= \frac{\tau_i^{\min}(s,\dot{s}) - c_i(s)\dot{s}^2 - g_i(s)}{m_i(s)} \\ -\text{If } m_i(s) &> 0: \\ U_i(s,\dot{s}) &= \frac{\tau_i^{\max}(s,\dot{s}) - c_i(s)\dot{s}^2 - g_i(s)}{m_i(s)} \\ L_i(s,\dot{s}) &= \frac{\tau_i^{\max}(s,\dot{s}) - c_i(s)\dot{s}^2 - g_i(s)}{m_i(s)} \\ -\text{If } m_i(s) &< 0: \\ U_i(s,\dot{s}) &= \frac{\tau_i^{\min}(s,\dot{s}) - c_i(s)\dot{s}^2 - g_i(s)}{m_i(s)} \end{aligned}$$

By defining  $L(s,\dot{s}) = \max_{i} L_i(s,\dot{s})$  and  $U(s,\dot{s}) = \min_{i} U_i(s,\dot{s})$  as the lower and upper bounds on  $\ddot{s}$  at  $(s, \dot{s})$ , (5) can be written as  $L(s, \dot{s}) \leq \ddot{s} \leq U(s, \dot{s})$ 



### **Time-optimal Time-scaling Problem**

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Given a path \theta(s), s \in [0,1], an initial state (s_0, \dot{s}_0) = (0,0), and a final state (s_f, \dot{s}_f) =
(1,0), find a monotonically increasing twice-differentiable time-scaling s(t), s:[0,t_f] \rightarrow
[0,1] that
               s(0) = \dot{s}(0) = \dot{s}(t_f) = 0 and s(t_f) = 1,
(a) satisfies:
(b) minimizes the total travel time t_f along the path while respecting the actuator
constraints:
                                    L(s,\dot{s}) \leq \ddot{s} \leq U(s,\dot{s})
               \equiv \dot{s}(t) \geq 0 (robot moves only forward along the path)
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This problem is easily visualized in the  $(s, \dot{s})$  phase plane.

Time-Optimal Time Scaling

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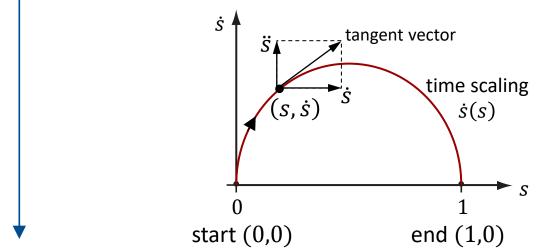
# $(s, \dot{s})$ Phase Plane



# $(s, \dot{s})$ Phase Plane

 $(s, \dot{s})$  phase plane is defined as a plane with s running from 0 to 1 on a horizontal axis and  $\dot{s}$  on a vertical axis.

A time scaling s(t) of the path is <u>any curve</u>  $\dot{s}(s)$  in the phase plane that moves monotonically to the right from (0,0) to (1,0) in the top-right quadrant.



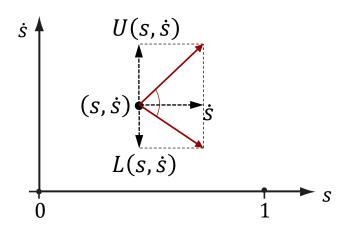
Among all these curves, we are looking for a time-optimal curve that satisfy the actuator/acceleration constraints  $L(s, \dot{s}) \leq \ddot{s} \leq U(s, \dot{s})$ .



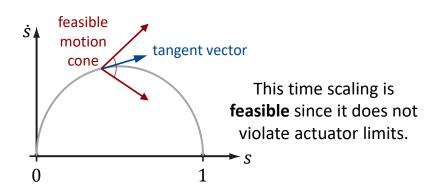
#### **Feasible Motion Cone**

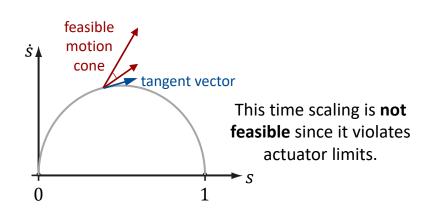
By drawing the range of feasible accelerations  $L(s,\dot{s}) \leq \ddot{s} \leq U(s,\dot{s})$  according to the dynamics at any state  $(s, \dot{s})$ , we find a cone called the feasible motion cone.

**Note**: Vector  $\dot{s}$  is proportional to the height of the point along the  $\dot{s}$  axis.



At each state  $(s, \dot{s})$ , the tangent vector to the time scaling  $\dot{s}(s)$  must lie **inside feasible** motion cone to satisfy the actuator limits (or the acceleration constraints).



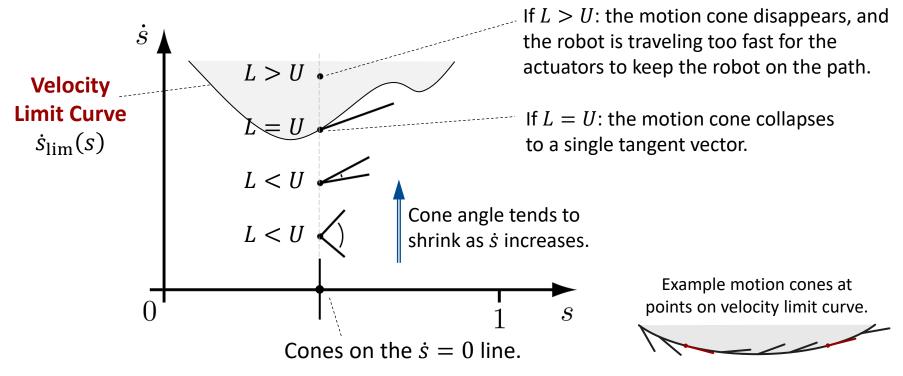


Time-Optimal Time Scaling



#### **Velocity Limit Curve**

Let keep *s* constant but increase *s* from 0:



At states on velocity limit curve, only <u>a single acceleration</u> is possible; at states above this curve, the robot leaves the path immediately (inadmissible states); and at states below the curve, there is a cone of possible tangent vectors (admissible states).



#### **Bang-Bang Time Scaling**

The total time of motion  $t_f$  can be written as

$$t_f = \int_0^{t_f} 1dt = \int_0^{t_f} \frac{ds}{ds} dt = \int_0^1 \frac{dt}{ds} ds = \int_0^1 \dot{s}^{-1}(s) ds$$

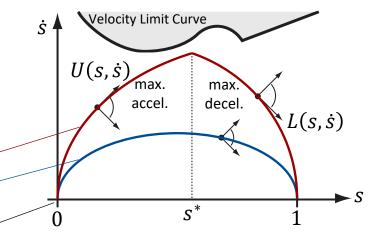
For a minimum-time motion,  $\dot{s}^{-1}$  should be as small as possible, and therefore,  $\dot{s}$  must be <u>as large as possible</u>, at all s, while still satisfying the acceleration constraints  $L(s,\dot{s}) \leq \ddot{s} \leq U(s,\dot{s})$  and the boundary constraints  $s(0) = \dot{s}(0) = \dot{s}(t_f) = 0$ ,  $s(t_f) = 1$ .

This implies that the time scaling must always operate either at the limit  $U(s,\dot{s})$  (the upper edge of the motion cones) or at the limit  $L(s,\dot{s})$  (the lower edge of the motion cones), and we should determine switching point  $s^*$  between these limits.

Time-optimal "bang-bang" time scaling

An example of a non-optimal time scaling

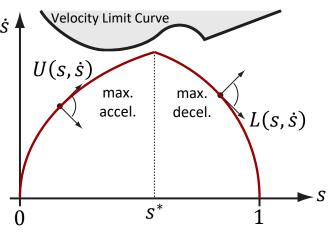
The curve must be normal to the s-axis when  $\dot{s} = 0$ .



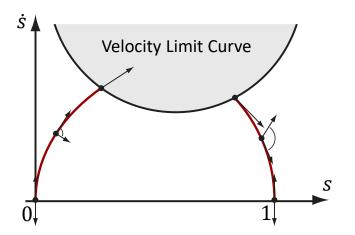


#### **Bang-Bang Time Scaling**

In general, the time scaling is calculated by numerically integrating  $\ddot{s} = U(s, \dot{s})$  (the maximum possible accelerations) forward in s from (0,0), integrating  $\ddot{s} = L(s, \dot{s})$  (the maximum possible decelerations) backward in s from (1,0), and finding the intersection (switching point  $s^*$ ) of these curves.



However, in some cases, the existence of a velocity limit curve prevents a single-switch solution (two curves do not intersect and run into the velocity limit curve). In these cases, bang-bang control is not possible, and it requires an algorithm to find multiple switching points.



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# **Time-Scaling Algorithm**

## **Time-Scaling Algorithm**

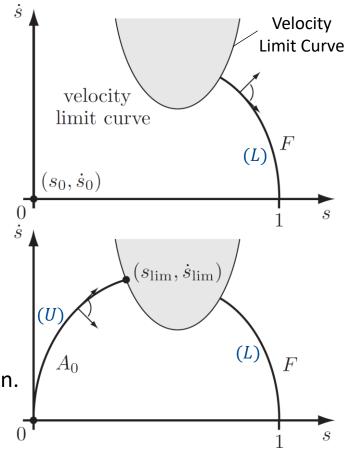
Since time-optimal trajectories consist of only maximum acceleration  $U(s,\dot{s})$  and minimum acceleration  $L(s,\dot{s})$ , we need to find the switches between U and L:

**Step 0**: Find the velocity limit curve.

**Step 1**: Integrate  $\ddot{s} = L(s, \dot{s})$  backward in time from (1,0) until (i) the velocity limit curve is penetrated  $(L(s, \dot{s}) > U(s, \dot{s}))$  or (ii) s = 0. Call this curve F.

**Step 2**: Integrate  $\ddot{s} = U(s, \dot{s})$  forward in time from (0,0) until (i) it intersects F or (ii) until the velocity limit curve is penetrated  $(L(s, \dot{s}) > U(s, \dot{s}))$ . Call this curve  $A_0$ .

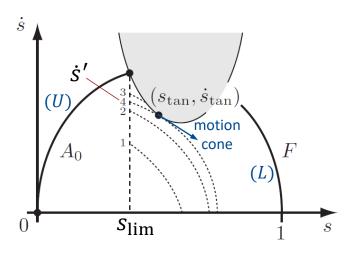
- If (i) happens, the problem is solved.
- If (ii) happens, let  $(s_{\lim}, \dot{s}_{\lim})$  be the point of penetration.



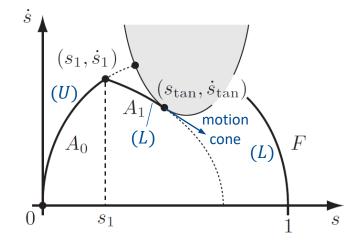


### **Time-Scaling Algorithm**

**Step 3**: Perform a <u>binary search</u> (or half-interval search) on the velocity in the range  $[0, \dot{s}_{\lim}]$  at  $s_{\lim}$  to find the velocity  $\dot{s}'$  such that the curve integrating  $\ddot{s} = L(s, \dot{s})$  forward in time from  $(s_{\lim}, \dot{s}')$  touches the velocity limit curve tangentially (or comes closest to the curve within a specified tolerance without hitting it) at  $(s_{\tan}, \dot{s}_{\tan})$ .



**Step 4**: Integrate  $\ddot{s} = L(s,\dot{s})$  backward in time from  $(s_{\tan},\dot{s}_{\tan})$  until it intersects  $A_0$  at  $(s_1,\dot{s}_1)$ . Call this curve  $A_1$ .  $(s_1,\dot{s}_1)$  is the first switch point from maximum acceleration to maximum deceleration.



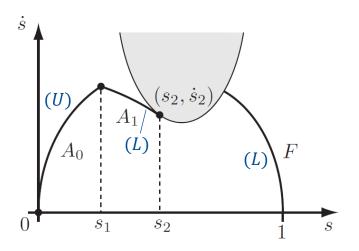


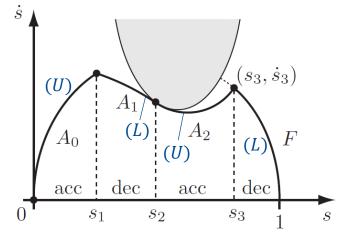
## **Time-Scaling Algorithm**

**Step 5**: Mark the tangent point  $(s_{tan}, \dot{s}_{tan})$  as the switch point  $(s_2, \dot{s}_2)$  from maximum deceleration to maximum acceleration.

**Step 6**: Go back to **Step 2**, i.e., integrate  $\ddot{s} = U(s, \dot{s})$  forward in time from  $(s_2, \dot{s}_2)$  until (i) it intersects F or (ii) until the velocity limit curve is penetrated again  $(L(s, \dot{s}) > U(s, \dot{s}))$ . Call this curve  $A_2$ .

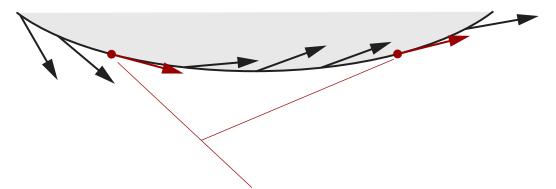
- If (i) happens, the intersection point  $(s_3, \dot{s}_3)$  is the final switch point from maximum acceleration to maximum deceleration and the algorithm is complete.
- If (ii) happens, let  $(s_{\lim}, \dot{s}_{\lim})$  be the new point of penetration and repeat the process from **Step 3**.





#### **Another Method to Find Switch Points on Velocity Limit Curve**

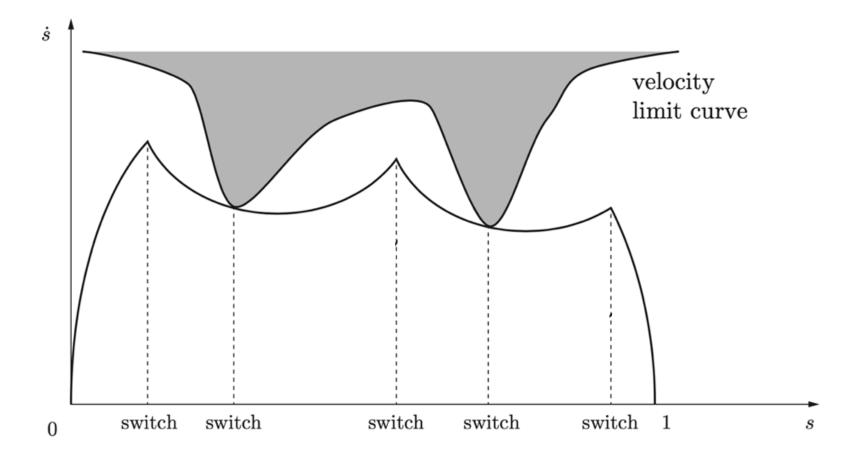
The only points on the velocity limit curve  $(L(s,\dot{s})=U(s,\dot{s}))$  that can be part of an optimal solution are those where the feasible motion vector  $(\dot{s}, U(s, \dot{s}))$  is tangent to the velocity limit curve  $(s_{tan}, \dot{s}_{tan})$ . Therefore, the binary search in the time-scaling algorithm (step 3) can be replaced by a more computationally efficient approach of numerical construction of the velocity limit curve and a searching on this curve for points where the motion vector is tangent to the curve.



The points that can belong to a time-optimal time scaling.

Time-Optimal Time Scaling

#### An Example of Multi-Switch Time-Optimal Time Scaling





#### **Example**

Draw the feasible time-optimal timescaling for a driver rushing home with the max braking and max acceleration integral curves shown.

