

Complementary note on:

# Application of the VFO extend procedure to sampling-based motion planning for mobile robots with bounded curvature of motion

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## Abstract

This note is complementing the results presented in conference paper [1] by providing detailed derivations of relations presented in the conference paper.

## 1 Introduction

Notational conventions from [1] are maintained in this note. References to equations from [1] will be enclosed in double parentheses. Unless stated otherwise, perfect motion execution by the VFO controller will be assumed throughout this document, that is  $e_{ai}^{i+1}(t) \equiv 0$ . The sign function used in the sequel is defined as follows

$$\text{sign}(x) \triangleq \begin{cases} 1 & \text{for } x \geq 0, \\ -1 & \text{for } x < 0. \end{cases} \quad (1)$$

## 2 Analytic prediction of robot's motion

### 2.1 Derivation of differential equations

We will now begin the detailed derivation of motion prediction curve ((19)). From the definition of  $u_2$  in ((6)) one has

$$u_2 \triangleq \rho_i \sigma_i \cos(e_{ai}^{i+1}). \quad (3)$$

Moreover, in ((10)) convergence vector field  $\bar{\mathbf{h}}_i^{i+1}$  was defined:

$$\bar{\mathbf{h}}_i^{i+1} \triangleq \begin{bmatrix} h_{xi}^{i+1} \\ h_{yi}^{i+1} \end{bmatrix} = -k_p \bar{\mathbf{q}}^{i+1} + \bar{\mathbf{v}}_i^{i+1} = -k_p \begin{bmatrix} x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\| \\ y^{i+1} \end{bmatrix}. \quad (4)$$

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Observe that, since  $e_{ai}^{i+1} \equiv 0 \Rightarrow \theta^{i+1} \equiv \theta_{ai}^{i+1}$ , the following relations hold:

$$\cos(\theta^{i+1}) = \cos(\theta_{ai}^{i+1}) \stackrel{(9)}{=} \cos(\text{Atan2c}(\sigma_i h_{yi}^{i+1}, \sigma_i h_{xi}^{i+1})) = \sigma_i \frac{h_{xi}^{i+1}}{\|\bar{\mathbf{h}}_i^{i+1}\|}, \quad (5)$$

$$\sin(\theta^{i+1}) = \sin(\theta_{ai}^{i+1}) \stackrel{(9)}{=} \sin(\text{Atan2c}(\sigma_i h_{yi}^{i+1}, \sigma_i h_{xi}^{i+1})) = \sigma_i \frac{h_{yi}^{i+1}}{\|\bar{\mathbf{h}}_i^{i+1}\|}, \quad (6)$$

$$\dot{\mathbf{q}}^{i+1} = u_2 \begin{bmatrix} \cos(\theta^{i+1}) \\ \sin(\theta^{i+1}) \end{bmatrix} \stackrel{(3)}{=} \rho_i \sigma_i \cos(e_{ai}^{i+1}) \begin{bmatrix} \cos(\theta^{i+1}) \\ \sin(\theta^{i+1}) \end{bmatrix} \stackrel{(5),(6)}{=} \frac{\rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} \begin{bmatrix} h_{xi}^{i+1} \\ h_{yi}^{i+1} \end{bmatrix}. \quad (7)$$

Since for  $e_{ai}^{i+1} \equiv 0$  robot's motion direction, and in consequence the considered prediction curve, depends only on  $\theta_{ai}^{i+1}$  and  $\forall S > 0 \text{ Atan2c}(Sy, Sx) = \text{Atan2c}(y, x)$ , the integral curve does not depend on the choice of  $\rho_i > 0$ . That is why one can assume  $\rho_i = \|\bar{\mathbf{h}}_i^{i+1}\|$ , and simplify (7) to  $\dot{\mathbf{q}}^{i+1} = \bar{\mathbf{h}}_i^{i+1}$ . As a consequence relations ((15)) and ((16)) hold:

$$\dot{y}^{i+1} \stackrel{(7)}{=} -k_p y^{i+1} \Rightarrow y^{i+1} = y_i^{i+1} \exp(-k_p \tau_i), \quad (8)$$

$$\dot{x}^{i+1} \stackrel{(7)}{=} -k_p (x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|). \quad (9)$$

## 2.2 Solution of differential equations - the prediction curve

Now, (9) will be solved by considering two cases. It is known from (8), that

$$y_i^{i+1} = 0 \Rightarrow \forall t \geq 0 \quad y^{i+1} = 0 \quad (10)$$

for every motion segment. Thus, for  $y_i^{i+1} = 0$  equation (9) degenerates to

$$\dot{x}^{i+1} = -k_p (1 + \sigma_i \mu_i \text{sign}(x^{i+1})) x^{i+1}, \quad (11)$$

which implies convergence of  $x^{i+1}(t)$  to 0, since  $(1 + \sigma_i \mu_i \text{sign}(x^{i+1})) > 0$ . Based on that, one concludes that for  $y_i^{i+1} = 0$ , closed-loop system follows the straight line  $y = 0$ .

When  $y_i^{i+1} \neq 0$ , we utilize a substitution  $x^{i+1} = z_i y^{i+1}$  in (9) to obtain:

$$\dot{z}_i y^{i+1} + \dot{y}^{i+1} z_i = -k_p \left( z_i y^{i+1} + \sigma_i \mu_i \sqrt{z_i^2 (y^{i+1})^2 + (y^{i+1})^2} \right) \Rightarrow \quad (12)$$

$$\dot{z}_i y^{i+1} + \dot{y}^{i+1} z_i = -k_p y^{i+1} \left( z_i + \sigma_i \mu_i \text{sign}(y^{i+1}) \sqrt{(z_i)^2 + 1} \right), \quad (13)$$

which can be further simplified using (8):

$$(\dot{z}_i - k_p z_i) y^{i+1} = -k_p y^{i+1} \left( z_i + \sigma_i \mu_i \text{sign}(y^{i+1}) \sqrt{(z_i)^2 + 1} \right) \Rightarrow \quad (14)$$

$$\dot{z}_i = -k_p \sigma_i \mu_i \text{sign}(y^{i+1}) \sqrt{(z_i)^2 + 1} \Rightarrow \quad (15)$$

$$\frac{dz_i}{\sqrt{(z_i)^2 + 1}} = -k_p \sigma_i \mu_i \text{sign}(y^{i+1}) d\tau_i, \quad (16)$$

which after integrating both sides yields:

$$\text{arsinh}(z_i) = -k_p \sigma_i \mu_i \text{sign}(y^{i+1}) \tau_i + C_i, \quad (17)$$

where  $C_i$  is the integration constant, while  $\tau_i \triangleq t - t_i$  denotes time from the beginning of  $i$ -th motion segment execution. It is evident that  $\tau_i = 0 \Rightarrow C_i = \operatorname{arsinh} \left( \frac{x_i^{i+1}}{y_i^{i+1}} \right)$ ,  $\operatorname{sign}(y_i^{i+1}) \stackrel{(8)}{=} \operatorname{sign}(y_i^{i+1})$ , and  $z_i = x_i^{i+1}/y_i^{i+1}$  by definition, which is why (17) can be transformed to ((17)):

$$x^{i+1}(\tau_i) = \sinh[-k_p \beta_i \mu_i \tau_i + C_i] y^{i+1}(\tau_i), \quad (18)$$

$$C_i = \operatorname{arsinh} \left( \frac{x_i^{i+1}}{y_i^{i+1}} \right), \quad \beta_i \triangleq \sigma_i \operatorname{sign}(y_i^{i+1}). \quad (19)$$

### 2.3 Curve parametrization

There are infinitely many pairs  $(x_i^{i+1}, y_i^{i+1})$  corresponding to the same value of constant  $C_i$  (cf. (19)) and in consequence corresponding to the same integral curve (18). To achieve a more convenient (i.e. unique) curve parametrization and express curve (18) as a function of  $y^{i+1}$ , we will compute the value of  $y^{i+1}$ , for which  $Y^{i+1}$  axis is crossed by integral curve (18). Let us use (18) and solve the equation w.r.t.  $\tau_i$  for  $x^{i+1} = 0$  to compute the time at which  $Y^{i+1}$  axis will be crossed:

$$0 = \sinh \left[ -k_p \sigma_i \mu_i \operatorname{sign}(y_i^{i+1}) \tau_i + \operatorname{arsinh} \left( \frac{x_i^{i+1}}{y_i^{i+1}} \right) \right] y^{i+1} \Rightarrow \quad (20)$$

$$k_p \mu_i \sigma_i \operatorname{sign}(y_i^{i+1}) \tau_i = \operatorname{arsinh} \left( \frac{x_i^{i+1}}{y_i^{i+1}} \right) \Rightarrow \quad (21)$$

$$\tau_i = \frac{\operatorname{arsinh}(x_i^{i+1}/y_i^{i+1})}{k_p \mu_i \sigma_i \operatorname{sign}(y_i^{i+1})}, \quad (22)$$

and eliminate time using (8) as follows

$$y^{i+1} = y_i^{i+1} \exp(-k_p \tau_i) \Rightarrow \quad (23)$$

$$\exp(-k_p \tau_i) = \frac{y^{i+1}}{y_i^{i+1}} \Rightarrow \quad (24)$$

$$\tau_i = \frac{-1}{k_p} \ln \left( \frac{y^{i+1}}{y_i^{i+1}} \right), \quad (25)$$

to obtain

$$\frac{-1}{k_p} \ln \left( \frac{y^{i+1}}{y_i^{i+1}} \right) \stackrel{(22),(25)}{=} \frac{\operatorname{arsinh}(x_i^{i+1}/y_i^{i+1})}{k_p \mu_i \sigma_i \operatorname{sign}(y_i^{i+1})} \Rightarrow \quad (26)$$

$$\ln \left( \frac{y^{i+1}}{y_i^{i+1}} \right) = \frac{\operatorname{arsinh}(x_i^{i+1}/y_i^{i+1})}{-\mu_i \sigma_i \operatorname{sign}(y_i^{i+1})} \Rightarrow \quad (27)$$

$$y^{i+1} = \exp \left( \frac{\operatorname{arsinh}(x_i^{i+1}/y_i^{i+1})}{-\mu_i \sigma_i \operatorname{sign}(y_i^{i+1})} \right) y_i^{i+1} \Rightarrow \quad (28)$$

$$\psi_i = \exp \left( \frac{-\operatorname{arsinh}(x_i^{i+1}/y_i^{i+1})}{\mu_i \sigma_i \operatorname{sign}(y_i^{i+1})} \right) y_i^{i+1} \Rightarrow \quad (29)$$

$$\psi_i \triangleq \exp \left( \frac{-C_i}{\mu_i \beta_i} \right) y_i^{i+1}, \quad (30)$$

where curve parameter  $\psi_i \neq 0$  corresponds to  $y^{i+1} \neq 0$  such that  $x^{i+1} = 0$ . It means that curve (18) crosses  $Y^{i+1}$  axis at point  $(0, \psi_i)$ . Such a point exists for every curve described by (18) and can be computed from (30), which is why one can assume  $y_i^{i+1} := \psi_i$  and  $x_i^{i+1} := 0$  in (18) without loss of generality and obtain:

$$x^{i+1} \stackrel{(18)}{=} \sinh \left[ -k_p \sigma_i \mu_i \text{sign} (y_i^{i+1}) \tau_i \right] y^{i+1} \stackrel{(25)}{\Rightarrow} \quad (31)$$

$$x^{i+1} = \sinh \left[ \sigma_i \mu_i \text{sign} (y_i^{i+1}) \ln \left( \frac{y^{i+1}}{y_i^{i+1}} \right) \right] y^{i+1} \stackrel{(8)}{\Rightarrow} \quad (32)$$

$$x^{i+1} = \sigma_i \sinh \left[ \mu_i \ln \left( \frac{y^{i+1}}{y_i^{i+1}} \right) \right] |y^{i+1}| \stackrel{y_i^{i+1} := \psi_i}{\Rightarrow} \quad (33)$$

$$x^{i+1} = \sigma_i \sinh \left[ \mu_i \ln \left( \frac{y^{i+1}}{\psi_i} \right) \right] |y^{i+1}|, \quad (34)$$

which can be transformed to ((19)) using the definition of sinh:

$$x^{i+1} (y^{i+1}) = \frac{\sigma_i |y^{i+1}|}{2} \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right], \quad (35)$$

where  $\psi_i$  is given by (30) and corresponds to a particular value of  $y^{i+1}$  when  $x^{i+1} = 0$ . Integral curve (35) describes robot's motion in perfect conditions, i.e. when  $e_{ai}^{i+1} = 0$  and the auxiliary orientation  $\theta_{ai}^{i+1}$  is tracked perfectly by robot's orientation  $\theta^{i+1}$ . Robot will move along curve (35) regardless of chosen velocity profile  $\rho_i > 0$ .

**Remark 1** *Negative time  $\tau_i$  can be obtained during some calculations. It corresponds to valid positions on the integral curve, which will not be traversed by the robot in the particular motion segment. They could be traversed if the beginning of motion segment (i.e point  $(x_i^{i+1}, y_i^{i+1})$ ) was placed on the same integral curve, but further away from the  $(i+1)$ -st waypoint.*

### 3 Satisfaction of curvature constraint

Let us derive equation ((21)) describing curvature of convergence vector field  $\bar{\mathbf{h}}_i^{i+1}$ . From definition of control input  $\mathbf{u}$  one has:

$$\kappa_i = \frac{u_1}{u_2} = \frac{\dot{\theta}_{ai}^{i+1}}{\sigma_i \rho_i} = \frac{\dot{h}_{yi}^{i+1} h_{xi}^{i+1} - \dot{h}_{xi}^{i+1} h_{yi}^{i+1}}{\sigma_i \rho_i ||\bar{\mathbf{h}}_i^{i+1}||^2}. \quad (36)$$

Moreover, assuming  $e_{ai}^{i+1} \equiv 0$ , one can write:

$$\dot{h}_{yi}^{i+1} \stackrel{(4)}{=} -k_p \dot{y}^{i+1} \stackrel{(7)}{=} -k_p \rho_i \frac{h_{yi}^{i+1}}{\|\bar{\mathbf{h}}_i^{i+1}\|} \stackrel{(4)}{=} k_p^2 \rho_i \frac{y^{i+1}}{\|\bar{\mathbf{h}}_i^{i+1}\|}, \quad (37)$$

$$\dot{h}_{yi}^{i+1} h_{xi}^{i+1} \stackrel{(37),(4)}{=} \frac{-k_p^3 \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} (x^{i+1} y^{i+1} + y^{i+1} \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|), \quad (38)$$

$$\begin{aligned} \dot{h}_{xi}^{i+1} &\stackrel{(4)}{=} -k_p \left( \dot{x}^{i+1} + \sigma_i \mu_i \frac{\dot{x}^{i+1} x^{i+1} + \dot{y}^{i+1} y^{i+1}}{\|\bar{\mathbf{q}}^{i+1}\|} \right) \\ &\stackrel{(7)}{=} \frac{-k_p \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} \left( h_{xi}^{i+1} + \sigma_i \mu_i \frac{h_{xi}^{i+1} x^{i+1} + h_{yi}^{i+1} y^{i+1}}{\|\bar{\mathbf{q}}^{i+1}\|} \right) \\ &\stackrel{(4)}{=} \frac{k_p^2 \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} \left( (x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|) + \sigma_i \mu_i \frac{(y^{i+1})^2 + x^{i+1} (x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|)}{\|\bar{\mathbf{q}}^{i+1}\|} \right) \\ &= \frac{k_p^2 \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} \left( x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\| + \sigma_i \mu_i \frac{\|\bar{\mathbf{q}}^{i+1}\|^2 + \sigma_i \mu_i x^{i+1} \|\bar{\mathbf{q}}^{i+1}\|}{\|\bar{\mathbf{q}}^{i+1}\|} \right) \\ &= \frac{k_p^2 \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} (x^{i+1} + 2\sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\| + \mu_i^2 x^{i+1}), \end{aligned} \quad (39)$$

$$\dot{h}_{xi}^{i+1} h_{yi}^{i+1} \stackrel{(39),(4)}{=} \frac{-k_p^3 \rho_i}{\|\bar{\mathbf{h}}_i^{i+1}\|} [2\sigma_i \mu_i y^{i+1} \|\bar{\mathbf{q}}^{i+1}\| + x^{i+1} y^{i+1} (1 + \mu_i^2)], \quad (40)$$

hence:

$$\begin{aligned} \kappa_i &\stackrel{(36)}{=} \frac{\dot{h}_{yi}^{i+1} h_{xi}^{i+1} - \dot{h}_{xi}^{i+1} h_{yi}^{i+1}}{\sigma_i \rho_i \|\bar{\mathbf{h}}_i^{i+1}\|^2} \\ &\stackrel{(38),(40)}{=} \frac{-k_p^3}{\sigma_i \|\bar{\mathbf{h}}_i^{i+1}\|^3} [x^{i+1} y^{i+1} + y^{i+1} \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\| - 2\sigma_i \mu_i y^{i+1} \|\bar{\mathbf{q}}^{i+1}\| - x^{i+1} y^{i+1} (1 + \mu_i^2)] \\ &= \frac{-k_p^3}{\sigma_i \|\bar{\mathbf{h}}_i^{i+1}\|^3} [-\mu_i^2 x^{i+1} y^{i+1} - y^{i+1} \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|] \\ &= \frac{k_p^3}{\sigma_i \|\bar{\mathbf{h}}_i^{i+1}\|^3} y^{i+1} [\mu_i^2 x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|], \end{aligned} \quad (41)$$

but since from the definition of  $\bar{\mathbf{h}}_i^{i+1}$  we have:

$$\begin{aligned} \|\bar{\mathbf{h}}_i^{i+1}\| &= \sqrt{(h_{xi}^{i+1})^2 + (h_{yi}^{i+1})^2} \\ &\stackrel{(4)}{=} \sqrt{k_p^2 (x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|)^2 + k_p^2 (y^{i+1})^2} \\ &= \sqrt{k_p^2 [(x^{i+1})^2 + 2\sigma_i \mu_i x^{i+1} \|\bar{\mathbf{q}}^{i+1}\| + \mu_i^2 \|\bar{\mathbf{q}}^{i+1}\|^2] + k_p^2 (y^{i+1})^2} \\ &= \sqrt{k_p^2 [(x^{i+1})^2 + (y^{i+1})^2 + \mu_i^2 \|\bar{\mathbf{q}}^{i+1}\|^2 + 2\sigma_i \mu_i x^{i+1} \|\bar{\mathbf{q}}^{i+1}\|]} \\ &= \sqrt{k_p^2 [\|\bar{\mathbf{q}}^{i+1}\|^2 + \mu_i^2 \|\bar{\mathbf{q}}^{i+1}\|^2 + 2\sigma_i \mu_i x^{i+1} \|\bar{\mathbf{q}}^{i+1}\|]} \\ &= k_p \|\bar{\mathbf{q}}^{i+1}\| \sqrt{1 + \mu_i^2 + 2\sigma_i \mu_i x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|}, \end{aligned} \quad (42)$$

one can write:

$$\kappa_i \stackrel{(41),(42)}{=} \frac{y^{i+1} (\mu_i^2 x^{i+1} + \sigma_i \mu_i \|\bar{\mathbf{q}}^{i+1}\|)}{\sigma_i \|\bar{\mathbf{q}}^{i+1}\|^3 \sqrt{1 + \mu_i^2 + 2\sigma_i \mu_i x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|}} \Rightarrow \quad (43)$$

$$\kappa_i (x^{i+1}, y^{i+1}) = \frac{\mu_i y^{i+1}}{\|\bar{\mathbf{q}}^{i+1}\|^2} m_i (\bar{\mathbf{q}}^{i+1}), \quad (44)$$

$$m_i (\bar{\mathbf{q}}^{i+1}) = \frac{\sigma_i + \mu_i (x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|)}{\sigma_i \sqrt{1 + \mu_i^2 + 2\sigma_i \mu_i (x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|)}} \quad (45)$$

as in ((21)).

In [1] we define  $\hat{m}_i \triangleq \lim_{\bar{\mathbf{q}}^{i+1} \rightarrow \mathbf{0}} m_i (\bar{\mathbf{q}}^{i+1}) = \text{const}$  used in analysis of limit ((22)). This claim is verified by examining definition of  $m_i (\bar{\mathbf{q}}^{i+1})$  in (45) and taking into account that:

- $\sigma_i \neq 0$ ,
- $\forall (x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|) \quad 1 + \mu_i^2 + 2\sigma_i \mu_i (x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|) \neq 0$ ,
- $\lim_{\bar{\mathbf{q}}^{i+1} \rightarrow \mathbf{0}} x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\| = \text{sign} (x_i^{i+1})$  along integral curve (35).

It remains to show that  $\lim_{\bar{\mathbf{q}}^{i+1} \rightarrow \mathbf{0}} x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\| = 1$  along integral curve (35). Let us recall that  $\text{sign} (x^{i+1}) = \text{sign} (x_i^{i+1})$  (cf. (35)) and compute

$$\begin{aligned} x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\| &= \text{sign} (x^{i+1}) \sqrt{(x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|)^2} \\ &= \text{sign} (x_i^{i+1}) \sqrt{(x^{i+1} / \|\bar{\mathbf{q}}^{i+1}\|)^2} \\ &= \text{sign} (x_i^{i+1}) \sqrt{\left( \frac{x^{i+1}}{\sqrt{(x^{i+1})^2 + (y^{i+1})^2}} \right)^2} \\ &\stackrel{(35)}{=} \text{sign} (x_i^{i+1}) \sqrt{\left( \frac{0.5 \sigma_i |y^{i+1}| \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]}{\sqrt{0.25 |y^{i+1}|^2 \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]^2 + (y^{i+1})^2}} \right)^2} \\ &= \text{sign} (x_i^{i+1}) \sqrt{\left( \frac{\sigma_i \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]}{\sqrt{\left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]^2 + 1}} \right)^2} \\ &= \text{sign} (x_i^{i+1}) \sqrt{\frac{\left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]^2}{D \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]^2 + D}}, \quad (46) \end{aligned}$$

$$D \triangleq \text{sign} \left( \left[ \left( \frac{y^{i+1}}{\psi_i} \right)^{\mu_i} - \left( \frac{y^{i+1}}{\psi_i} \right)^{-\mu_i} \right]^2 + 1 \right), \quad (47)$$

which can be simplified to

$$\begin{aligned}
x^{i+1}/\|\bar{\mathbf{q}}^{i+1}\| &\stackrel{(46)}{=} \text{sign}(x_i^{i+1}) \sqrt{\frac{\left(\frac{y^{i+1}}{\psi_i}\right)^{-2\mu_i} \left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2}{\left(\frac{y^{i+1}}{\psi_i}\right)^{-2\mu_i} \left\{ D \left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2 + D \left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} \right\}}} \\
&= \text{sign}(x_i^{i+1}) \sqrt{\frac{\left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2}{D \left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2 + D \left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i}}}, \tag{48}
\end{aligned}$$

hence

$$\begin{aligned}
\lim_{\bar{\mathbf{q}}^{i+1} \rightarrow \mathbf{0}} x^{i+1}/\|\bar{\mathbf{q}}^{i+1}\| &\stackrel{(48)}{=} \lim_{\bar{\mathbf{q}}^{i+1} \rightarrow \mathbf{0}} \text{sign}(x_i^{i+1}) \sqrt{\frac{\left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2}{D \left[\left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i} - 1\right]^2 + D \left(\frac{y^{i+1}}{\psi_i}\right)^{2\mu_i}}} \\
&= \text{sign}(x_i^{i+1}) \sqrt{\frac{1}{D}} \stackrel{(47)}{=} \text{sign}(x^{i+1}). \tag{49}
\end{aligned}$$

### 3.1 Curvature scaling

To verify that for a constant  $S > 0$  one can write  $\kappa_i(Sx^{i+1}, Sy^{i+1}) = \kappa_i(x^{i+1}, y^{i+1})/S$  we observe that

$$x^{i+1}/\|\bar{\mathbf{q}}^{i+1}\| = Sx^{i+1}/\|S\bar{\mathbf{q}}^{i+1}\|. \tag{50}$$

This relation implies that  $m_i(\bar{\mathbf{q}}^{i+1}) = m_i(S\bar{\mathbf{q}}^{i+1})$  (cf. (45)). It is now evident that

$$\kappa_i(Sx^{i+1}, Sy^{i+1}) = \frac{\mu_i Sy^{i+1}}{S^2 \|\bar{\mathbf{q}}^{i+1}\|^2} m_i(\bar{\mathbf{q}}^{i+1}) = \kappa_i(x^{i+1}, y^{i+1})/S. \tag{51}$$

To show that  $\kappa_i$  along prediction curve (35) is inversely proportional to  $\psi_i$  one must show that both  $x^{i+1}(y^{i+1})$  and  $y^{i+1}$  (cf. (35)) scale linearly with  $\psi_i$ . Let us recall that  $\psi_i$  corresponds to a particular value of  $y^{i+1}$  when  $x^{i+1} = 0$ , hence by definition  $y^{i+1}$  scales linearly with  $\psi_i$ . If one considers that  $y^{i+1}/\psi_i$  is constant under scaling, because  $y^{i+1}$  scales linearly with  $\psi_i$ , it can be seen from (35) that  $x^{i+1}(Sy^{i+1}) = Sx^{i+1}(y^{i+1})$ . After considering the above claims, one concludes that  $\kappa_i$  along prediction curve (35) is indeed inversely proportional to  $\psi_i$ , which means that we must compute only particular curvature supremum  $\mathcal{K}_i(0, 1)$  and use

$$\mathcal{K}_i(x_i^{i+1}, y_i^{i+1}) = \mathcal{K}_i(0, \psi_i) = \mathcal{K}_i(0, 1)/\psi_i, \tag{52}$$

for other cases. Note that such a solution is general, since  $\psi_i$  can be computed for any integral curve using (30).  $\mathcal{K}_i(0, 1)$  represents maximal curvature of motion along a particular integral curve described by (35) with  $\psi_i = 1$ . One might interpret this

particular curve as an archetype of all other integral curves described by (35). All other integral curves can be obtained by scaling of this curve. The scaling corresponds to different values of parameter  $\psi_i$ . We will show how to compute  $\mathcal{K}_i(0,1)$  in the next subsection.

### 3.2 Maximum of curvature

To find  $\mathcal{K}_i(0,1) = \kappa_i(x^{i+1}(\hat{y}^{i+1}), \hat{y}^{i+1})$  (cf. ((24))), one must only compute  $\hat{y}^{i+1}$  corresponding to the point at which maximum of curvature is reached by curve (35). The value of  $x^{i+1}(\hat{y}^{i+1})$  is given by (35).

**Remark 2** *There is an editing error in initial submission of paper [1], eq. ((24)) - there should be:  $\mathcal{K}_i(0,1) = \kappa_i(x^{i+1}(\hat{y}^{i+1}), \hat{y}^{i+1})$ .*

To simplify the notation, we will assume  $\mathcal{Y} \equiv |y^{i+1}|$  in the sequel. We begin the derivation of the exact value of  $\hat{y}^{i+1}$  by substituting (35) into (44) and taking  $x_i^{i+1} = 0 \wedge \psi_i = 1$  (because  $\mathcal{K}_i(0,1)$  must be computed) to obtain:

$$\tilde{\kappa}(\mathcal{Y}) \stackrel{(35)}{=} \frac{4\mu_i(\mu_i\mathcal{Y}^{2\mu_i} - \mu_i + \mathcal{Y}^{2\mu_i} + 1)}{\mathcal{Y}^{\mu_i+1} \left( \frac{(\mu_i + \mu_i\mathcal{Y}^{2\mu_i} + \mathcal{Y}^{2\mu_i} - 1)^2}{\mathcal{Y}^{2\mu_i}} + 4 \right)^{\frac{3}{2}}}, \quad (53)$$

where  $\tilde{\kappa}(\mathcal{Y})$  denotes curvature along the considered particular integral curve, which can be differentiated to write

$$\frac{d}{dy^{i+1}} \tilde{\kappa} = -\frac{N}{M} = 0, \quad (54)$$

where:

$$\begin{aligned} N = & 4\mu_i(2\mu_i\mathcal{Y}^{4\mu_i} - 2\mu_i\mathcal{Y}^{2\mu_i} - 2\mu_i + 2\mu_i\mathcal{Y}^{6\mu_i} - 3\mu_i + 3\mathcal{Y}^{2\mu_i} + \\ & 3\mathcal{Y}^{4\mu_i} + \mathcal{Y}^{6\mu_i} + 2\mu_i^3 - \mu_i^4 + 2\mu_i^3\mathcal{Y}^{2\mu_i} - 3\mu_i^4\mathcal{Y}^{2\mu_i} - 2\mu_i^3\mathcal{Y}^{4\mu_i} - 3\mu_i^4\mathcal{Y}^{4\mu_i} - \\ & 2\mu_i^3\mathcal{Y}^{6\mu_i} - \mu_i^4\mathcal{Y}^{6\mu_i} + 9\mu_i^2 - 9\mu_i^3 + 3\mu_i^4 - 3\mu_i\mathcal{Y}^{2\mu_i} + 3\mu_i\mathcal{Y}^{4\mu_i} + 3\mu_i\mathcal{Y}^{6\mu_i} + \\ & 3\mu_i^2\mathcal{Y}^{2\mu_i} + 3\mu_i^3\mathcal{Y}^{2\mu_i} + 3\mu_i^2\mathcal{Y}^{4\mu_i} - 3\mu_i^4\mathcal{Y}^{2\mu_i} - 3\mu_i^3\mathcal{Y}^{4\mu_i} + \\ & 9\mu_i^2\mathcal{Y}^{6\mu_i} - 3\mu_i^4\mathcal{Y}^{4\mu_i} + 9\mu_i^3\mathcal{Y}^{6\mu_i} + 3\mu_i^4\mathcal{Y}^{6\mu_i} + 1), \end{aligned} \quad (55)$$

$$M = \mathcal{Y}^{3\mu_i+2}(2\mu_i\mathcal{Y}^{2\mu_i} - 2\mu_i\mathcal{Y}^{-2\mu_i} + \mathcal{Y}^{-2\mu_i} + \mathcal{Y}^{2\mu_i} + 2\mu_i^2 + \mu_i^2\mathcal{Y}^{-2\mu_i} + \mu_i^2\mathcal{Y}^{2\mu_i} + 2)^{\frac{5}{2}}. \quad (56)$$

Since  $\mathcal{Y} \neq 0 \Rightarrow M \neq 0$ , we can solve  $N = 0$  instead. Solution of this equation is ((25)). It can be obtained by utilizing a substitution  $\mathcal{Y}^{2\mu_i} = v$  in the equation  $N = 0$  and solving the resulting cubic polynomial

$$\begin{aligned} & 4\mu_i[v^3(2\mu_i^4 + 7\mu_i^3 + 9\mu_i^2 + 5\mu_i + 1) + v^2(-6\mu_i^4 - 5\mu_i^3 + 3\mu_i^2 + 5\mu_i + 3) + \\ & v(-6\mu_i^4 + 5\mu_i^3 + 3\mu_i^2 - 5\mu_i + 3) + 2\mu_i^4 - 7\mu_i^3 + 9\mu_i^2 - 5\mu_i + 1] = 0 \end{aligned} \quad (57)$$

w.r.t.  $\mathcal{Y}$  to obtain  $\hat{y}^{i+1}$ . Polynomial (57) has one real root  $\hat{y}^{i+1}$  and two conjugate complex roots, hence  $\mathcal{K}_i$  is maximum of curvature in  $i$ -th motion segment.



It remains to show that  $\mathcal{Y} \neq 0 \Rightarrow M \neq 0$ . Let us factorize  $M$  as follows

$$\begin{aligned}
M &\stackrel{(56)}{=} \mathcal{Y}^{3\mu_i+2} \{ \mathcal{Y}^{-2\mu_i} (\mathcal{Y}^{2\mu_i} + 1) [\mathcal{Y}^{2\mu_i} (\mu_i^2 + 2\mu_i + 1) + (\mu_i^2 - 2\mu_i + 1)] \}^{\frac{5}{2}} \\
&= \mathcal{Y}^{3\mu_i+2} \{ \mathcal{Y}^{-2\mu_i} (\mathcal{Y}^{2\mu_i} + 1) [\mathcal{Y}^{2\mu_i} (\mu_i + 1)^2 + (\mu_i - 1)^2] \}^{\frac{5}{2}} \\
&= \mathcal{Y}^{2-2\mu_i} \{ (\mathcal{Y}^{2\mu_i} + 1) [\mathcal{Y}^{2\mu_i} (\mu_i + 1)^2 + (\mu_i - 1)^2] \}^{\frac{5}{2}}.
\end{aligned} \tag{58}$$

It follows from (58) that  $M = 0$  iff

$$\mathcal{Y} = 0 \quad \vee \quad \mathcal{Y} = (-1)^{\frac{1}{2\mu_i}} \quad \vee \quad \mathcal{Y} = \left( -\frac{(\mu_i - 1)^2}{(\mu_i + 1)^2} \right)^{\frac{1}{2\mu_i}}, \tag{59}$$

which means that  $M$  will have value of 0 only when  $\mathcal{Y}$  will be either 0 or complex. We know that such a situation cannot occur by definition.

**Remark 3** *Using the reasoning from Subsection 3.1 one can express curvature along any integral curve (35) as*

$$\kappa_i(\mathcal{Y}) = \frac{\tilde{\kappa}(\mathcal{Y})}{\psi_i}. \tag{60}$$

## References

- [1] T. Gawron and M. M. Michałek. Application of the VFO extend procedure to sampling-based motion planning for mobile robots with bounded curvature of motion. Submitted to IROS 2015, March 2015.