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## **Reparameterizations and Lagrange piecewise-cubics for fitting reduced data**

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The problem of estimating the unknown regular curve  $\gamma : [0, T] \to \mathbb{E}^n$  from the so-called reduced data  $Q_m$  has been so far extensively studied in the related literature (see e.g. [1], [3] or [4]). In this setting,  $Q_m$  forms the collection of m + 1 points  $Q_m = \{q_i\}_{i=0}^m$  in arbitrary Euclidean space  $\mathbb{E}^n$  satisfying the corresponding interpolation conditions  $q_i = \gamma(t_i)$ . Having selected a specific scheme  $\hat{\gamma}$  to fit  $Q_m$  (see e.g. [1]), the unknown interpolation knots  $\mathcal{T}_m = \{t_i\}_{i=0}^m$  obeying  $t_i < t_{i+1}$  must be somehow compensated by their "estimates"  $\hat{\mathcal{T}}_m = \{t_i\}_{i=0}^m$  subject to  $\hat{t}_i < \hat{t}_{i+1}$ . Given  $Q_m$ , the appropriate choice of  $\hat{\mathcal{T}}_m$  should guarantee potentially a fast convergence rate  $\alpha$  in estimating  $\gamma$  by  $\hat{\gamma}$  at best matching the underlying asymptotics in  $\gamma \approx \hat{\gamma}$  as if the missing knots  $\mathcal{T}$  were used. A possible recipe for  $\hat{\mathcal{T}}_m \approx \mathcal{T}$  is to apply the so-called exponential parameterization  $\hat{\mathcal{T}}_m^\lambda = \{\hat{t}_{i,\lambda}\}_{i=0}^m$  controlled by  $Q_m$  and a single parameter  $\lambda \in [0, 1]$  - see e.g. [3]. A special case of  $\lambda = 1$  yields a well-known cumulative chord parameterization discussed e.g. in [2], [3], [4] or [11]. The asymptotics in approximating  $\gamma$  by various  $\hat{\gamma}$  based on  $(Q_m, \hat{\mathcal{T}}_m^\lambda)$  are studied e.g. in [2], [4], [5], [6] or [7]. In particular, for a modified Hermite interpolant  $\hat{\gamma} = \hat{\gamma}_H \in C^1$  (see [10]) and for an arbitrary  $\gamma \in C^4([0, T])$  the following sharp result holds, uniformly over [0, T] (see [4], [7] and [9]):

$$(\hat{\gamma}^H \circ \psi)(t) = \gamma(t) + O(\delta_m^1) \text{ for } \lambda \in [0, 1) \text{ and } (\hat{\gamma}^H \circ \psi)(t) = \gamma(t) + O(\delta_m^4) \text{ for } \lambda = 1, (1)$$

where  $\psi : [0, T] \to [0, \hat{T}]$  defined in [7] is implicitly parameterized by  $\lambda$  (here  $\hat{T} = \hat{t}_{m,\lambda}$ ). Here  $\delta_m = \min_{i \leq 0 \leq m-1} \{ t_{i+1} - t_i \}$ . The case of  $\lambda \in [0, 1)$  requires to assume a thinner class of *more-or-less uniform samplings* (see [6]), whereas  $\lambda = 1$  stipulates an admission of more general class of the so-called *admissible samplings* - see [4]. For certain applications  $\psi$  should constitute a genuine *reparameterization* (e.g. for length  $d(\gamma)$  estimation by  $d(\hat{\gamma})$ ). In other cases the mapping  $\psi$  needs to be *a non-injective mapping* (e.g. if extra loops in trajectory of  $\hat{\gamma} \circ \psi$  are required). The last issue is recently studied for  $\hat{\gamma}^H$  in [10]. An analogous asymptotics to (1) is established for Lagrange piecewise-cubics  $\hat{\gamma} = \hat{\gamma}^C \in C^0$  in [4], [8] and [11]. Here the mapping  $\psi = \psi^c : [0,T] \to [0,\hat{T}]$ , defines similarly a Lagrange piecewise-cubic satisfying  $\psi^c(t_i) = \hat{t}_{i,\lambda}$ .

In this work we formulate and prove sufficient conditions for  $\psi^c$  to yield  $\dot{\psi}^c > 0$  for both sparse and dense reduced data  $Q_m$ . The latter enforces  $\psi^c$  to be a reparameterization. Geometrical and algebraic insight supported by illustrative visualization is also given with the aid of symbolic computations performed in *Mathematica* [12].

## Keywords

Interpolation, Reduced data, Convergence, Sharpness and Parameterization

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