Robust exact differentiation

Let a signal f(t) be a function defined on $[0, \infty)$, which is a result of real-time noisy measurements of some unknown *n*-smooth signal $f_0(t)$ with the *n*th derivative $f_0^{(n)}(t)$ having a known Lipschitz constant L > 0. The function f(t) is assumed to be a Lebesgue-measurable function, the unknown sampling noise $f(t) - f_0(t)$ is assumed bounded. The task is to find real-time estimations of f_0 , \dot{f}_0 , \ddot{f}_0 , ..., $f_0^{(n)}$ using only values of f and the number L. The estimations are to be exact in the absence of noises when $f(t) = f_0(t)$.

Denote by $D_{n-1}(f(\cdot),L)$ the (n-1)th-order differentiator producing outputs $D_{n-1}^{i}(f(\cdot),L)$, i = 0, 1, ..., n-1, being estimations of f_0 , \dot{f}_0 , \ddot{f}_0 , ..., $f_0^{(n-1)}$ for any input f(t) with $f_0^{(n-1)}$ having Lipschitz constant L > 0. Then the *n*th-order differentiator has the outputs $z_i = D_n^i(f(\cdot),L)$, i = 0, 1, ..., n, defined recursively as follows:

$$\dot{z}_0 = v, \qquad v = -\lambda_n L^{1/(n+1)} |z_0 - f(t)|^{n/(n+1)} \operatorname{sign}(z_0 - f(t)) + z_1,$$

$$z_1 = D_{n-1}^0(v(\cdot), L), \quad \dots, \quad z_n = D_{n-1}^{n-1}(v(\cdot), L).$$

Here $D_0(f(\cdot), L)$ is a simple nonlinear filter

$$D_0: \quad \dot{z} = -\lambda_0 L \operatorname{sign}(z - f(t)), \qquad \lambda_0 > 1.$$

Thus, the *n*th-order differentiator [3] has the form

$$\dot{z}_{0} = v_{0}, \qquad v_{0} = -\lambda_{n} L^{1/(n+1)} |z_{0} - f(t)|^{n/(n+1)} \operatorname{sign}(z_{0} - f(t)) + z_{1}, \dot{z}_{1} = v_{1}, \qquad v_{1} = -\lambda_{n-1} L^{1/n} |z_{1} - v_{0}|^{(n-1)/n} \operatorname{sign}(z_{1} - v_{0}) + z_{2}, \dots \\ \dot{z}_{n-1} = v_{n-1}, \qquad v_{n-1} = -\lambda_{1} L^{1/2} |z_{n-1} - v_{n-2}|^{1/2} \operatorname{sign}(z_{n-1} - v_{n-2}) + z_{n}, \dot{z}_{n} = -\lambda_{0} L \operatorname{sign}(z_{n} - v_{n-1}),$$

$$(1)$$

where $\lambda_i > 0$ are chosen sufficiently large in the list order. The solution is understood in the Filippov sense [1]. Note that it contains actually all the lower-order differentiators and each recursive step requires tuning one parameter only. With n = 1 the first-order differentiator from [2] is obtained. The Theorem [3] actually states that there exists a sequence $\{\lambda_i\}$ suitable for all differentiators.

There is a simple, though rather conservative, algebraic criterion for the parameter choice when n = 1, a practically-exact simply-verified integral criterion is also available in that case [2]. Unfortunately, such criteria lack with n > 1. The author found a number of computer-checked parameter combinations for n = 5 and less. One of the combinations is $\lambda_0 = 1.1$, $\lambda_1 = 1.5$, $\lambda_2 = 3$, $\lambda_3 = 5$, $\lambda_4 = 8$, $\lambda_5 = 12$, another one is $\lambda_0 = 1.1$, $\lambda_1 = 1.5$, $\lambda_2 = 2$, $\lambda_3 = 3$, $\lambda_4 = 5$, $\lambda_5 = 8$. Following relations are established in finite time with properly chosen parameters [2, 3]:

1. if $f(t) = f_0(t)$ (there is no noise) then

$$z_0 = f_0(t);$$
 $z_i = v_{i-1} = f_0^{(i)}(t), \quad i = 1, ..., n;$

2. if $|f(t) - f_0(t)| \le \varepsilon$, then for some positive constants μ_i , ν_i depending exclusively on the parameters of differentiator (1)

$$\begin{aligned} |z_i - f_0^{(i)}(t)| &\leq \mu_i \, \varepsilon^{(n-i+1)/(n+1)}, \, i = 0, \, \dots, \, n, \\ |v_i - f_0^{(i+1)}(t)| &\leq \nu_i \, \varepsilon^{(n-i)/(n+1)}, \, i = 0, \, \dots, \, n\text{-}1; \end{aligned}$$

3. if $f(t) = f_0(t)$, but f(t) is sampled with a constant time period $\tau > 0$, then for some $\underline{\mu}_i, \underline{\nu}_i$

$$\begin{aligned} |z_i - f_0^{(i)}(t)| &\leq \underline{\mu}_i \ \tau^{n-i+1}, \ i = 0, \ \dots, \ n, \\ |v_i - f_0^{(i+1)}(t)| &\leq \underline{\nu}_i \ \tau^{n-i}, \ i = 0, \ \dots, \ n-1 \end{aligned}$$

It is easy to see that the *n*th order differentiator provides for a much better accuracy of the *l*th derivative, l < n, than the *l*th order differentiator. Thus, the additional smoothness of the unknown input signal $f_0(t)$ can be used to improve its derivative estimation based on the noisy measurement f(t).

Results of the 5th-order numerical differentiation of the signal $f_0(t) = 0.5 \sin 0.5t + 0.5 \cos t$ with $\lambda_0 = 1.1$, $\lambda_1 = 1.5$, $\lambda_2 = 3$, $\lambda_3 = 5$, $\lambda_4 = 8$, $\lambda_5 = 12$, L = 1 are shown in Fig. 1.

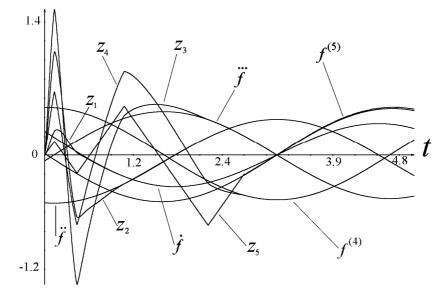


Fig. 1: 5th-order numerical differentiation

Numeric differentiation: instructions

In case $|f^{(n+1)}| \le L$ the *n*th order differentiator parameters are changed with respect to the rule $\lambda_i = \lambda_{0i} L^{1/(n-i+1)}$. Following are equations of the 5th-order differentiator with simulation-tested coefficients. As mentioned, it contains also differentiators of the lower orders:

$$\dot{z}_{0} = v_{0}, \quad v_{0} = -8 L^{1/6} |z_{0} - f(t)|^{5/6} \operatorname{sign}(z_{0} - f(t)) + z_{1},$$

$$\dot{z}_{1} = v_{1}, \quad v_{1} = -5 L^{1/5} |z_{1} - v_{0}|^{4/5} \operatorname{sign}(z_{1} - v_{0}) + z_{2},$$

$$\dot{z}_{2} = v_{2}, \quad v_{2} = -3 L^{1/4} |z_{2} - v_{1}|^{3/4} \operatorname{sign}(z_{2} - v_{1}) + z_{3},$$

$$\dot{z}_{3} = v_{3}, \quad v_{3} = -2 L^{1/3} |z_{3} - v_{2}|^{2/3} \operatorname{sign}(z_{3} - v_{2}) + z_{4},$$

$$\dot{z}_{4} = v_{4}, \quad v_{4} = -1.5 L^{1/2} |z_{4} - v_{3}|^{1/2} \operatorname{sign}(z_{4} - v_{3}) + z_{5},$$

$$\dot{z}_{5} = -1.1 L \operatorname{sign}(z_{5} - v_{4});$$

Here z_i are the estimations of $f^{(i)}(t)$, i = 0, ..., 5, $|f^{(6)}(t)| \le L$. The differentiator parameters can be easily changed. For example, increasing the gain in the line for \dot{z}_3 does not influence the coefficients for \dot{z}_4 and \dot{z}_5 , but may require some enlargement of the above gains. The tradeoff is as follows: the larger the parameters, the faster the convergence and the higher sensitivity to input noises and the sampling step.

For example, the second order differentiator for the input f with $|\ddot{f}| \le 1$ is

$$\dot{z}_{0} = v_{0}, \quad v_{0} = -2 |z_{0} - f|^{2/3} \operatorname{sign}(z_{0} - f) + z_{1},$$

$$\dot{z}_{1} = v_{1}, \quad v_{1} = -1.5 |z_{1} - v_{0}|^{1/2} \operatorname{sign}(z_{1} - v_{0}) + z_{2},$$

$$\dot{z}_{2} = -1.1 \operatorname{sign}(z_{2} - v_{1}).$$

In particular, with $|\ddot{f}| \le L$ the second order differentiator is

$$\dot{z}_{0} = v_{0}, \quad v_{0} = -2 L^{1/3} |z_{0} - f|^{2/3} \operatorname{sign}(z_{0} - f) + z_{1},$$

$$\dot{z}_{1} = v_{1}, \quad v_{1} = -1.5 L^{1/2} |z_{1} - v_{0}|^{1/2} \operatorname{sign}(z_{1} - v_{0}) + z_{2},$$

$$\dot{z}_{2} = -1.1 L \operatorname{sign}(z_{2} - v_{1});$$

and the first order differentiator with $|\ddot{f}| \le L$ is

$$\dot{z}_0 = v_0$$
, $v_0 = -1.5 L^{1/2} |z_0 - f|^{1/2} \operatorname{sign}(z_0 - f) + z_1$,
 $\dot{z}_1 = -1.1 L \operatorname{sign}(z_1 - v_0) = -1.1 L \operatorname{sign}(z_0 - f)$.

 z_0, z_1, z_2, \dots stay for the smoothed input f and its successive derivatives \dot{f} , \ddot{f} , ... respectively. The last equality in the second line is just an identity, showing the compliance with [2].

With discrete sampling the latter differentiator takes on the form

$$\dot{z}_0 = v_0, \quad v_0 = -1.5 L^{1/2} |z_0 - f(t_i)|^{1/2} \operatorname{sign}(z_0 - f(t_i)) + z_1,$$

$$\dot{z}_1 = -1.1 L \operatorname{sign}(z_1 - v_0(t_i)) = -1.1 L \operatorname{sign}(z_0 - f(t_i)),$$

where the current time *t* satisfies $t_i \le t \le t_i + \tau = t_{i+1}$.

In order to differentiate a real signal, one needs to estimate approximately the constant L and to use the smallest available integration and sampling time steps. It is important to check that the auxiliary variables $v_0, ..., v_{n-1}$ be calculated based on the values of z and f obtained at the last sampling time (no mixing!). At first L may be taken redundantly large, afterwards it can be gradually reduced during the simulation. The criterion for the good differentiation is that the output z_0 is to track the smoothed input, which is checked looking at the graph.

Important: integration by the Euler method!

References

- [1] Filippov A.F., *Differential Equations with Discontinuous Right-Hand Side*, Kluwer, Dordrecht, the Netherlands, (1988).
- [2] Levant A., Robust exact differentiation via sliding mode technique. *Automatica*, Vol. 34, No. 3, pp. 379-384, (1998).
- [3] Levant, A. (2003). Higher-order sliding modes, differentiation and output-feedback control, *International Journal of Control*, **76** (9/10), 924-941.