Filtering Performance Comparison of Kernel and Wavelet Filters for Reactivity Signal Noise

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1. Introduction

Nuclear reactor power deviation from the critical state is a parameter of specific interest defined by the reactivity measuring neutron population. Reactivity is an extremely important quantity used to define many of the reactor startup physics parameters. The timedependent reactivity is normally determined by solving the using inverse neutron kinetics equation. The reactivity computer is a device to provide an on-line solution of the inverse kinetics equation. The measurement signal of the neutron density is normally noise corrupted and the control rods movement typically gives reactivity variation with edge signals like saw teeth. Those edge regions should be precisely preserved since the measured signal is used to estimate the reactivity wroth which is a crucial parameter to assure the safety of the nuclear reactors.

In this paper, three kind of edge preserving noise filters are proposed and their performance is demonstrated using stepwise signals. The tested filters are based on the unilateral, bilateral kernel and wavelet filters which are known to be effective in edge preservation. The bilateral filter shows a remarkable improvement compared with unilateral kernel and wavelet filters.

2. Methods and Results

In this section some of the mathematical techniques and simulation results of kernel regression and wavelet filters are described.

2.1 Unilateral Kernel Filter

Kernel regression is an old method for smoothing data still new work continues at a rapid pace. Kernel regression of statistics was derived independently by Nadaraya[1] and Moore[2]. Kernel regression is the estimation of the functional relationship y(t) between two variables y and t. Measurement produces a set of random variables $\{t_i, y_i; i = 1, 2, ..., N\}$ on the interval $\{0 \le t_i \le T\}$. It is assumed that

$$y_i = y(t_i) + \varepsilon \tag{1}$$

where \mathcal{E} is a random noise variable with the mean equal to zero. The Nadaraya-Watson kernel regression estimate of y(t) at $t = \tau$ from this random data is defined as the estimator $\hat{y}(\tau)$ as

$$\hat{y}(\tau) = \frac{\sum_{i=1}^{N} y_i k(\tau - t_i)}{\sum_{i=1}^{N} k(\tau - t_i)}.$$
(2)

The function $k(\tau - t_i)$ is the kernel function which can

be chosen from a wide variety of symmetric functions. In this paper, the Gaussian density function is used, i.e.,

$$k(t) = \exp(-D(t_i, t_a)^2 / \sigma^2)$$
(3)

where D is the distance metric and Euclidean distance is used here defined by

$$D(t_i, t_q) = \left\| t_i - t_q \right\| = \sqrt{(t_i - t_q)^2}.$$
 (4)

 t_q is the query point where the smoothed signal is to be generated in the interval of time series data $\{0 \le t_i \le T\}$. σ^2 is the bandwidth of the kernel which controls how wide the influencing measurements are spread around a query point. Bandwidth can also control the smoothness or roughness of a density estimate. Increasing the kernel width σ^2 means further away points get an opportunity to influence the query point. As $\sigma^2 \rightarrow \infty$, the smoothed signal tends to the global average.

2.2 Bilateral Kernel Filter

The bilateral filter is a technique proposed by Tomasi and Manduchi[3]. This technique preserves edges by mixing a moving average technique with a nonlinear system of weights. It relies on an assumption that any noise is more uniformly distributed, and that signals have distinct edges or steps that can be detected by examining local differences. Each neighboring value is weighted on its proximity in space or time (a domain weight). But then, a second weighting factor gives some measurement of local difference (a range weight). Often, these two weights are expressed as a pair of Gaussian distributions in a summation. In the time domain, this is expressed as:

$$k(t) = k_D(\text{distance}) \times k_G(\text{feature})$$

= exp(-D(t_i, t_q)^2 / \sigma_t^2) \times exp(-D(y_i, y_q)^2 / \sigma_x^2) (5)

where σ_t^2 , σ_x^2 are the variances of the spatial distances for noise rejection and feature preservation, respectively. The weighting factor plays a role with local difference information for edge preservation.

2.3 Wavelet Filter

Wavelet is a waveform of effectively limited duration that has an average value of zero, which can be applied to non-stationary and transient signal. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. Arbitrary functions can be expressed as the sum of sub-functions which indicates the number of decomposition process of the time-domain signal. A basic theory of wavelet filter can be found in [4].

2.4 Results

Figure 1 shows the variation of reactivity signal and filtered signal of prescribed three noise filters. Figure 2 amd 3 show the magnified view of the filter performance at edge area. The bilateral filter gives excellent edge preserving property compared with unilateral or wavelet filters. This kind of stepwise variation of reactivity is frequently found during reactor startup physics test from movement of control rods. Therefore the reconstruction capability of the edge points is an important characteristic of the reactivity smoother.

Figure 4 shows the estimation error of the reactivity signal. The bilateral kernel filter gives very small estimation error even at edge regions.



Figure 1. Time-varying reactivity signal with edges



Figure 2. Edge signal at region A



Figure 3. Edge signal at region B



Figure 4. Error (reference-filtered)

3. Conclusion

The edge preserving performance of noise filters are demonstrated. The bilateral filter shows a remarkable improvement compared with unilateral kernel and wavelet filters. Those filters are developed and successfully applied to digital to reactivity computer system for reactor physics tests. The results show the developed filters can be applied not only the noise smoothing but also bumpless follow of the signal with non-smooth edges.

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