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Abstract

Modified Local Regression for Signal Resampling †

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Abstract: The resampling of sensor signals to compensate for deviating sampling intervals, clock jitter, or missing samples is still challenging. Real-time applications demand low latency and restriction of the input data window to past samples. Furthermore, most practical sensor signals are overlaid with noise. A new resampling method that provides a lower error than four other common interpolation methods under such conditions is introduced.

Keywords: non-uniform resampling; local polynomial regression; low-latency resampling

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1. Introduction

The measurement data from wireless sensors must often be resampled to comply with the requirements of subsequent signal processing. The Whittaker–Shannon interpolation [1] provides exact reconstruction only for optimal signal conditions, i.e., uniformly sampled signals with a band limit of half the sampling frequency (Nyquist frequency), infinite length, and absence of noise.

Most of these conditions are not fulfilled in real measurement tasks. Measurements contain noise. Especially for the task of real-time resampling with low latency [2], the window with the available measurements is restricted to past values. Furthermore, single measurements can be lost or delayed by communication problems, resulting in non-uniform sampling time points.

Alternate methods for non-uniform resampling entail high mathematical effort, e.g., Lagrange interpolation [3] requires the calculation of a high-order polynomial, and Kriging interpolation [4] is based on a matrix inversion of order equal to the window length. Akima interpolation [5] provides a simple solution. However, it requires the collection of three future samples ahead of the prediction target and is less accurate. Local polynomial regression (LPR) [6], also known as locally estimated scatterplot smoothing (LOESS), is less complex and does not require additional future samples. Each target point for the resampled signal is locally fitted using a square function. The input data are weighted using a tri-cube kernel. The square function can adapt well to the curve of a single peak, but it cannot use information from the previous peak of a periodic signal.

2. New Interpolation Method

We present a new local regression method based on Fourier approximation instead of polynomials. It applies the same local weighting process as in LPR. The set of base functions includes three or four pairs of sine and cos functions plus constant and linear elements. We call this method 'local Fourier regression' (LFR).

3. Test Method

Sine waves and bandlimited noise were applied as test signals. Test files for uniform sampling with an interval of T_S = 1 s, missing every 11th sample, or sampling with random jitter of max. $\pm 1/4\ T_S$ time deviations were created. Kriging, Lagrange, Akima, LPR, and LFR methods were applied to resample the signal to T_R = 0.1 s. The root-mean-square error

(RMSE) between the original and resampled signal was calculated. The input frequency or noise band limit was varied during a frequency sweep, and the RMSE was plotted as an indicator for the resampling accuracy. The noise sensitivity was tested by adding white noise with 0.001 (−60 dB) times the average amplitude of the input signal.

4. Results and Discussion

The real-time mode, with only past samples known, was the most critical case during the simulations and had the highest resampling error. An acceptable RMSE < 40 dB can only be achieved for a signal bandwidth $f_B < 0.3$ Hz, which is 1/3 less than the Nyquist frequency (Figure 1a). For the noise-free case, Kriging always performed better than LFR. Lagrange provides a lower error for $f_B < 0.12$ Hz but at the cost of a higher error at other frequencies.

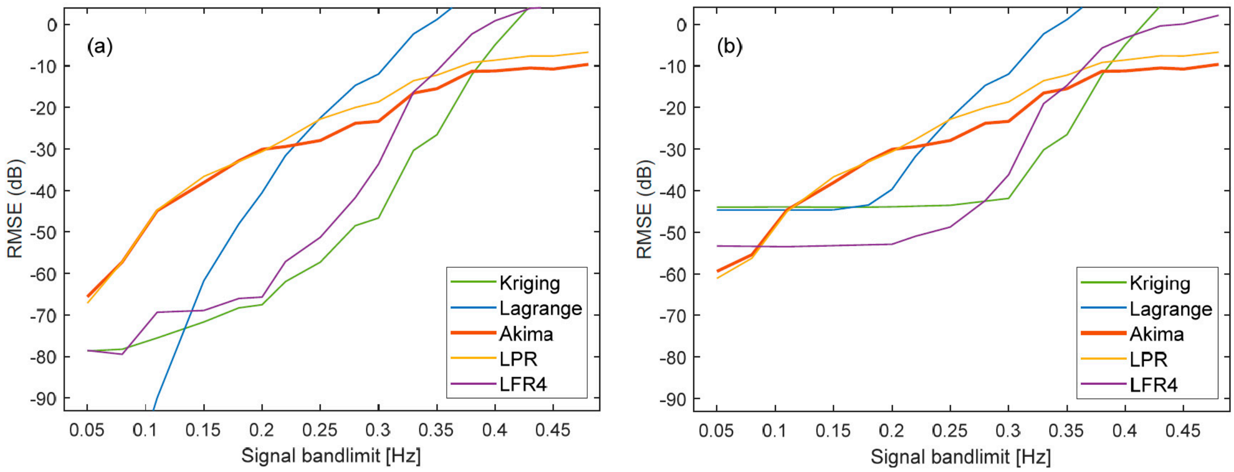

Figure 1. RMSE as a function of the band-limit test signal. Reconstruction for real-time mode with only past samples known. (**a**) Clean input signal. (**b**) Input signal overlaid with −60 dB white noise.

Kriging, Lagrange, and LFR turned out to be very noise-sensitive, with an RMSE of 7 dB to 14 dB above the noise floor (Figure 1b). Akima and LPR are less noise-sensitive but must be excluded due to their poor overall performance, except for $f_B < 0.09$ Hz. In general, LFR showed the best performance with an RMSE < −50 dB for $f_B < 0.25$ Hz.

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