# **Unlimited Sampling with Local Averages Recovery of High Dynamic Range Inputs from Average Samples**

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### Summary

- We address a fundamental bottleneck in physical sensors: dynamic range limitation.
- The limitation was mainly discussed in the traditional scenario of ideal point-wise sampling as part of the Unlimited Sensing Framework.
- In our hardware experiments we noticed a **deviation from the ideal sampling model**, particularly for signals with jump discontinuities.
- The observations are better described by a sampling model with local averages.
- We introduce a new average sampling architecture based on a nonlinear operator called *modulo-hysteresis* used recently for recovery from point-wise samples.
- We give theoretical recovery guarantees and show the performance of our method using hardware and synthetic data.

### The Unlimited Sensing Framework (USF)

• A conventional ADC saturates for inputs outside its dynamic range  $\Rightarrow$  permanent information loss; modulo encoding addresses this [2]:  $z(t) = \mathcal{M}_{\lambda}(g(t))$ ,  $k \in \mathbb{Z}$ .

**Theorem** (Unlimited Sampling Theorem – [2]). Let  $g(t) \in PW_{\Omega}$  and  $y_k =$  $\mathcal{M}_{\lambda}(g(t))|_{t=kT}, k \in \mathbb{Z}$  be the modulo samples of g(t) with sampling period T. Then, a sufficient condition for recovery of g(t) from the  $\{y_k\}$  up to additive multiples of  $2\lambda$  is



the USF approach is not applicable.







- $\mathbb{M}_N \triangleq \left\{ k \in \mathbb{Z} \mid \left| \Delta^N y[k] \right| \geq \frac{\lambda_h}{2N} \right\}$  is the set of samples displaced by modulo
- **Theorem 1 (Estimation of Folding Times).** Let  $k_m = \min \mathbb{M}_N$ . If  $\|\Delta^N g(t_k)\|_{\infty}$  $< \frac{\lambda_h}{2N}$  then

$$\widetilde{\tau}_1 = \widetilde{n}_1 T - 2\nu \widetilde{\beta}_1 + \nu \text{ and } \widetilde{s}_1 = -i$$

be the estimates of the folding time with  $\tilde{n}_1 = k_m + N$  and  $\beta_1$  where

$$\begin{cases} \widetilde{\beta}_{1} = \frac{\Delta^{N} y[k_{m}]}{2\lambda_{h} \widetilde{s}_{1}} & \text{if } \\ \widetilde{\beta}_{1} = 1 & \text{if } \\ \end{cases} \Delta^{N} y[k_{m}] \\ \Delta^{N} y[k_{m}] \end{cases}$$



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- $-\operatorname{sign}\left(\Delta^{N} y\left[k_{m}\right]\right)$ (1)

$$\left| \begin{array}{l} \leq 2\lambda_h - \frac{\lambda_h}{2N} \\ > 2\lambda_h - \frac{\lambda_h}{2N}. \end{array} \right.$$





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### Sampling at Low Rates

### References

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