

DIFFERENTIATE-AND-FIRE TIME-ENCODING OF FRI SIGNALS

Abijith J. Kamath and Chandra Sekhar Seelamantula

Department of Electrical Engineering

Indian Institute of Science, Bangalore

Email: {abijithj, css}@iisc.ac.in



Shannon Sampling

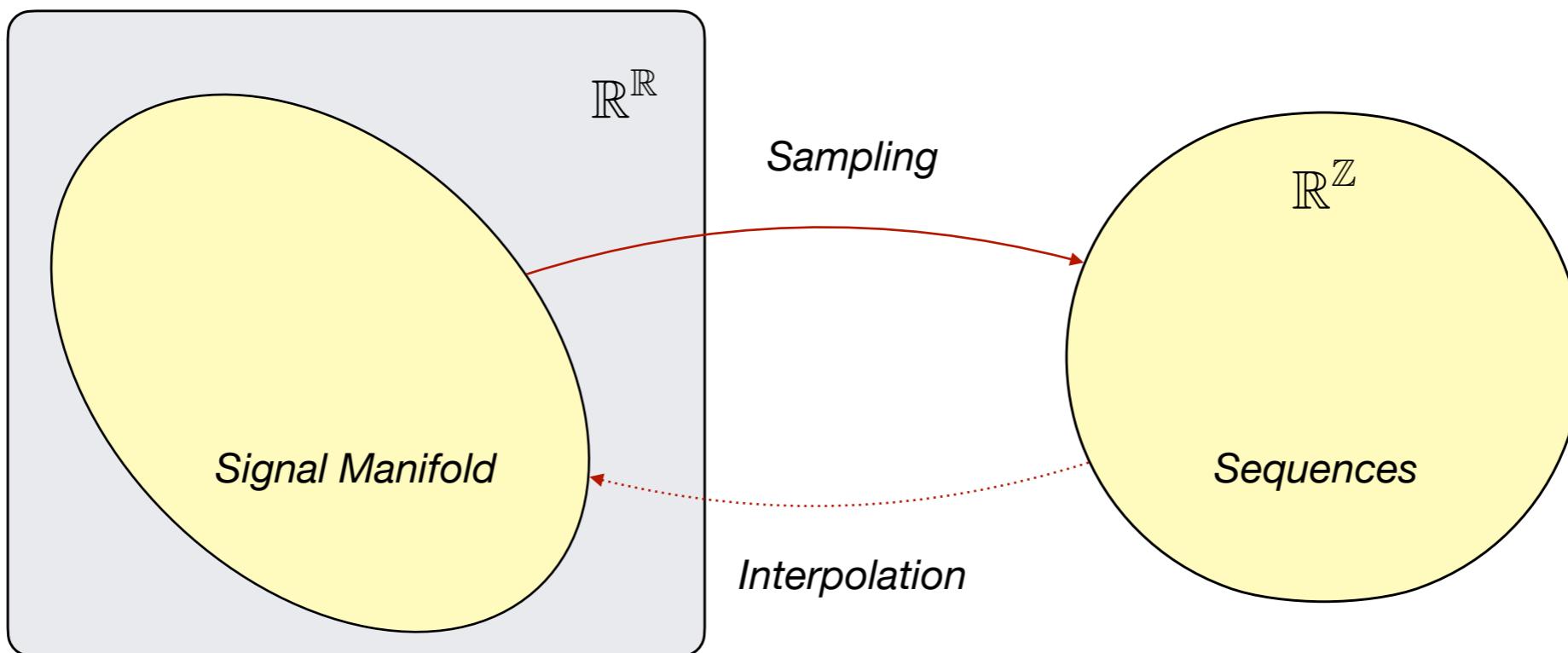
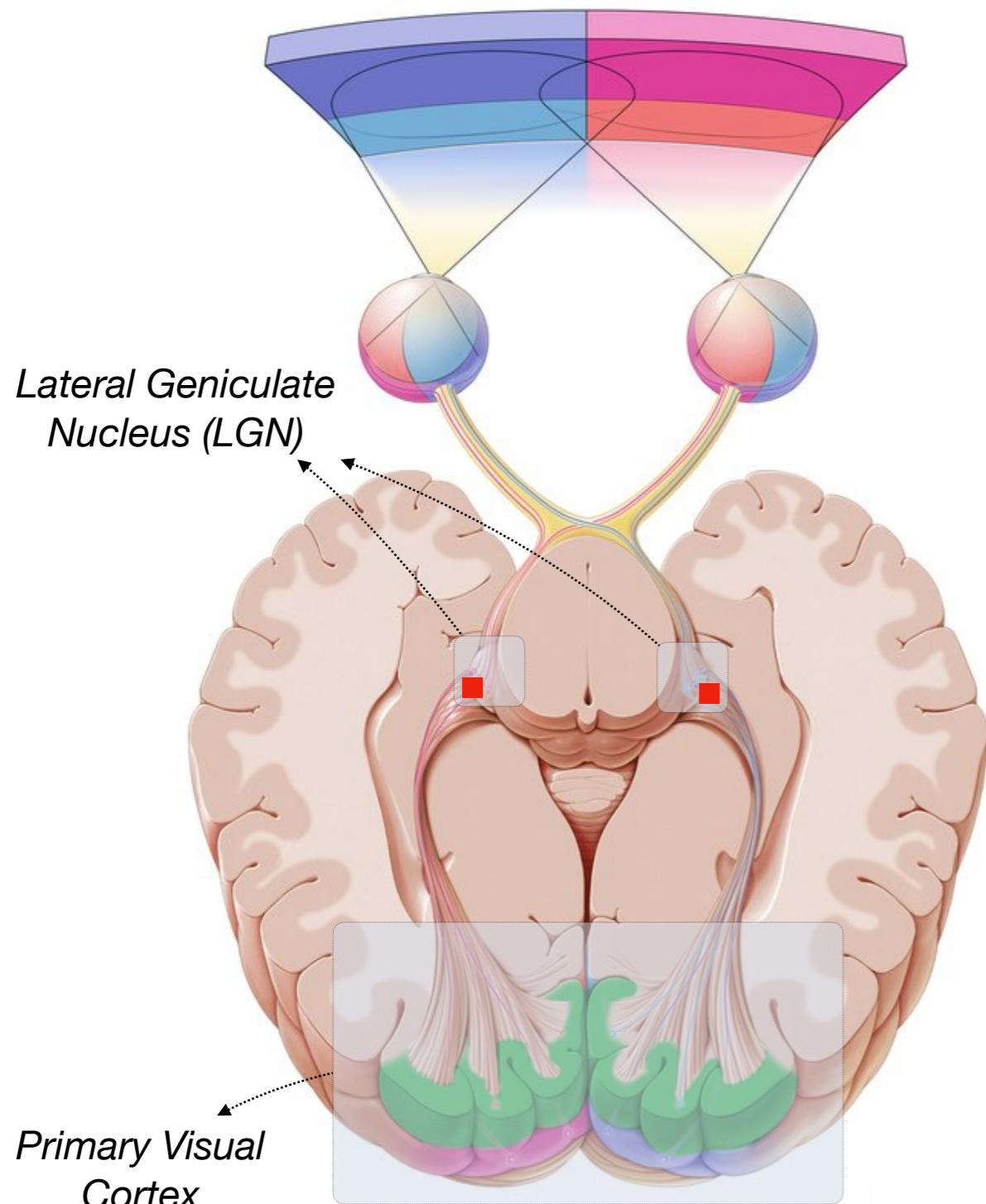


Fig 1: Sampling maps signal manifolds to sequences; interpolation maps sequences to signals

Theorem (Shannon, 1949)

If a function f contains no frequencies higher than ξ_N , it is completely described by giving its ordinates at a series of points spaced $T_s = \frac{1}{2\xi_N}$ apart.

Representation of Neural Signals



■ *Parvocellular Pathways* ↵ IF-TEM

- Sustained vision
- High spatial resolution
- Colour vision
- Low contrast vision

■ *Magnocellular Pathways* ↵ DIF-TEM

- Transient vision
- Low spatial resolution
- Monochrome vision
- High contrast vision

Fig 3: Schematic of the human visual system

Time-Encoding of Continuous-Time Signals

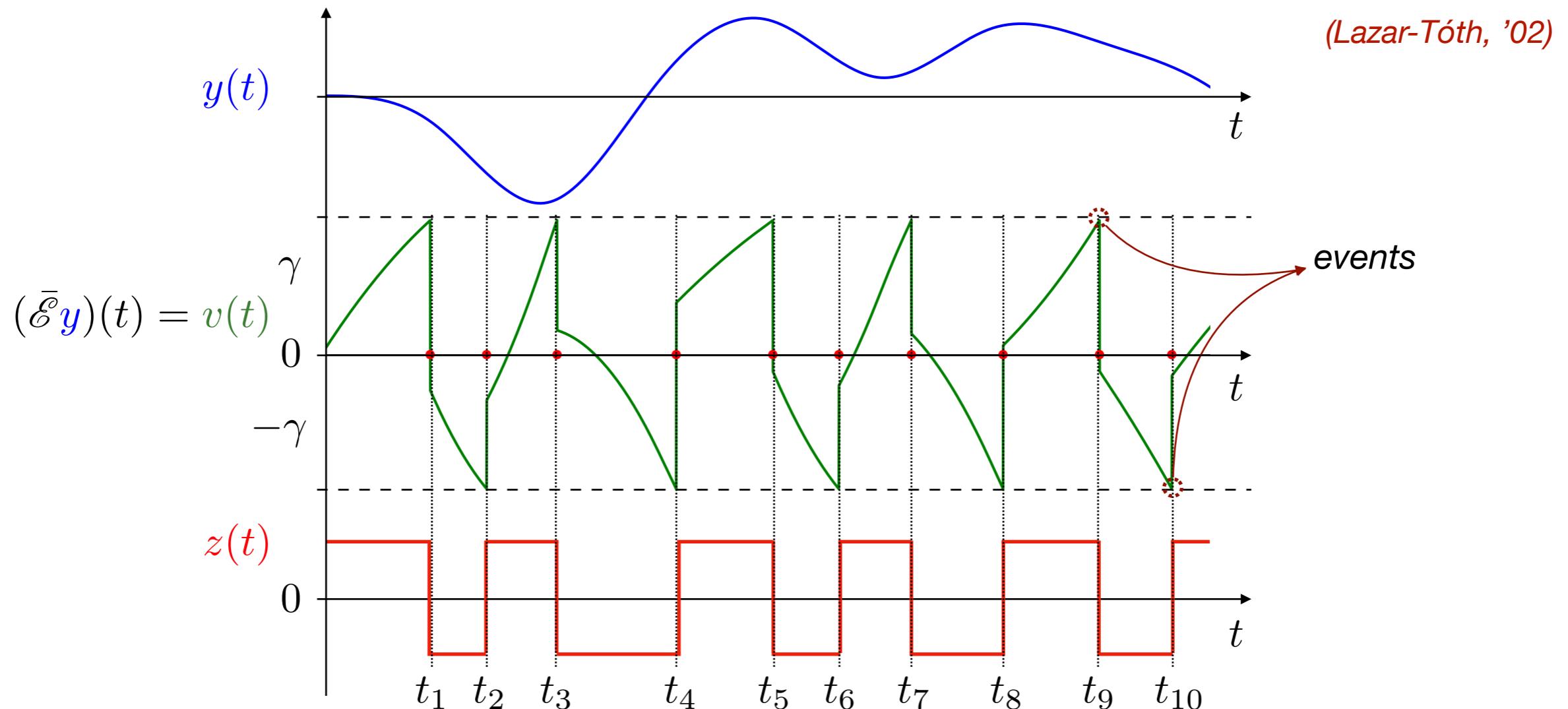


Fig 2: The concept of time-encoding of continuous-time signals

- Mimics peripheral perception of sensory signals
- Low power
- Sparse measurements
- Low redundancy

Time-Encoding Machines

Definition

(Kamath-CSS, '21)

A *time-encoding machine* is a map $\mathcal{T} : \mathbb{R}^{\mathbb{R}} \rightarrow \mathbb{R}^{\mathbb{Z}}$ with

- an event operator \mathcal{E} on $\mathbb{R}^{\mathbb{R}}$ and
- references $\{r_n\}_{n \in \mathbb{Z}}$

such that $y \mapsto \mathcal{T}y$ follows

- $\mathcal{T}y = \{t_i \in \mathbb{R} \mid t_i > t_j, \forall i > j, i \in \mathbb{Z}\}$ (ordering)
- $(\mathcal{E}y)(t_n) = r_n(t_n), \forall t_n \in \mathcal{T}y$ (characterization)

- *Sampling density* of $\mathcal{T}y$, $d(\mathcal{T}y) = \sup_{n \in \mathbb{Z}} |t_{n+1} - t_n|$
- $\mathcal{T}y$ is *ϵ -distinct* if $|t_{n+1} - t_n| > \epsilon, \forall n \in \mathbb{Z}$

Our Contributions

Part I Introduction

Part II The Differentiate-and-Fire Time-Encoding Machine

- t -transform
- Sampling sets of DIF-TEM

Part III Time-Encoding of FRI Signals Using DIF-TEM

- Kernel-based Time-Encoding
- Sufficient Conditions for Perfect Recovery

Part IV Simulation Results

Part V Conclusions and Future Work

Differentiate-and-Fire Time-Encoding Machine

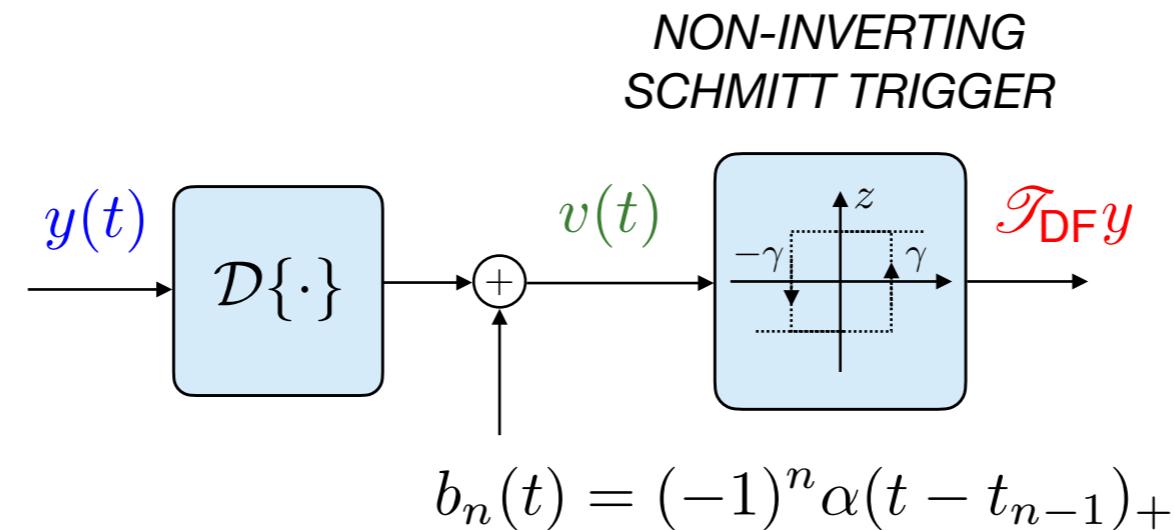


Fig 4: DIF-TEM with a bias signal $b_n(t)$ and threshold γ

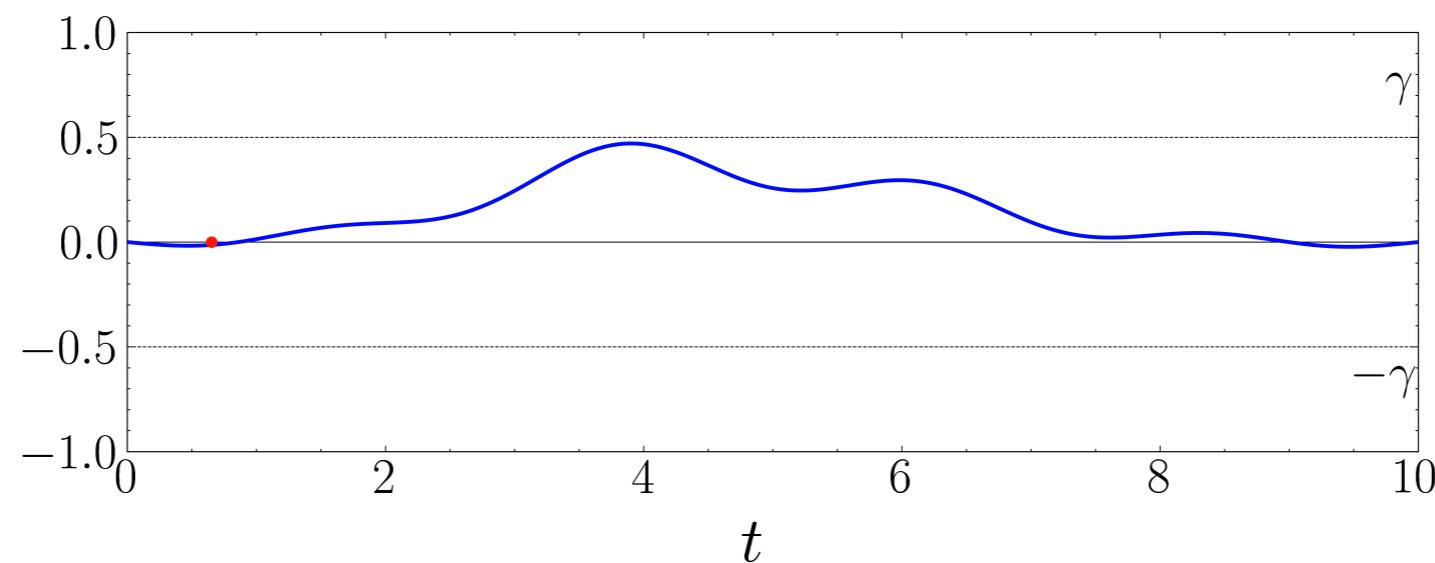


Fig 5: Demonstration of firing in DIF-TEM

Differentiate-and-Fire Time-Encoding Machine

Lemma (*t*-transform)

Let $y \in C^1(\mathbb{R})$ be the input to the DIF-TEM with parameters $\{\alpha, \gamma\}$.
The output of the DIF-TEM $\mathcal{T}_{\text{DF}}y = \{t_n\}_{n \in \mathbb{Z}}$ satisfies:

$$(\mathcal{D}y)(t_n) = (-1)^{n+1} (\gamma - \alpha(t_n - t_{n-1})), \quad \forall t_n \in \mathcal{T}_{\text{DF}}y.$$

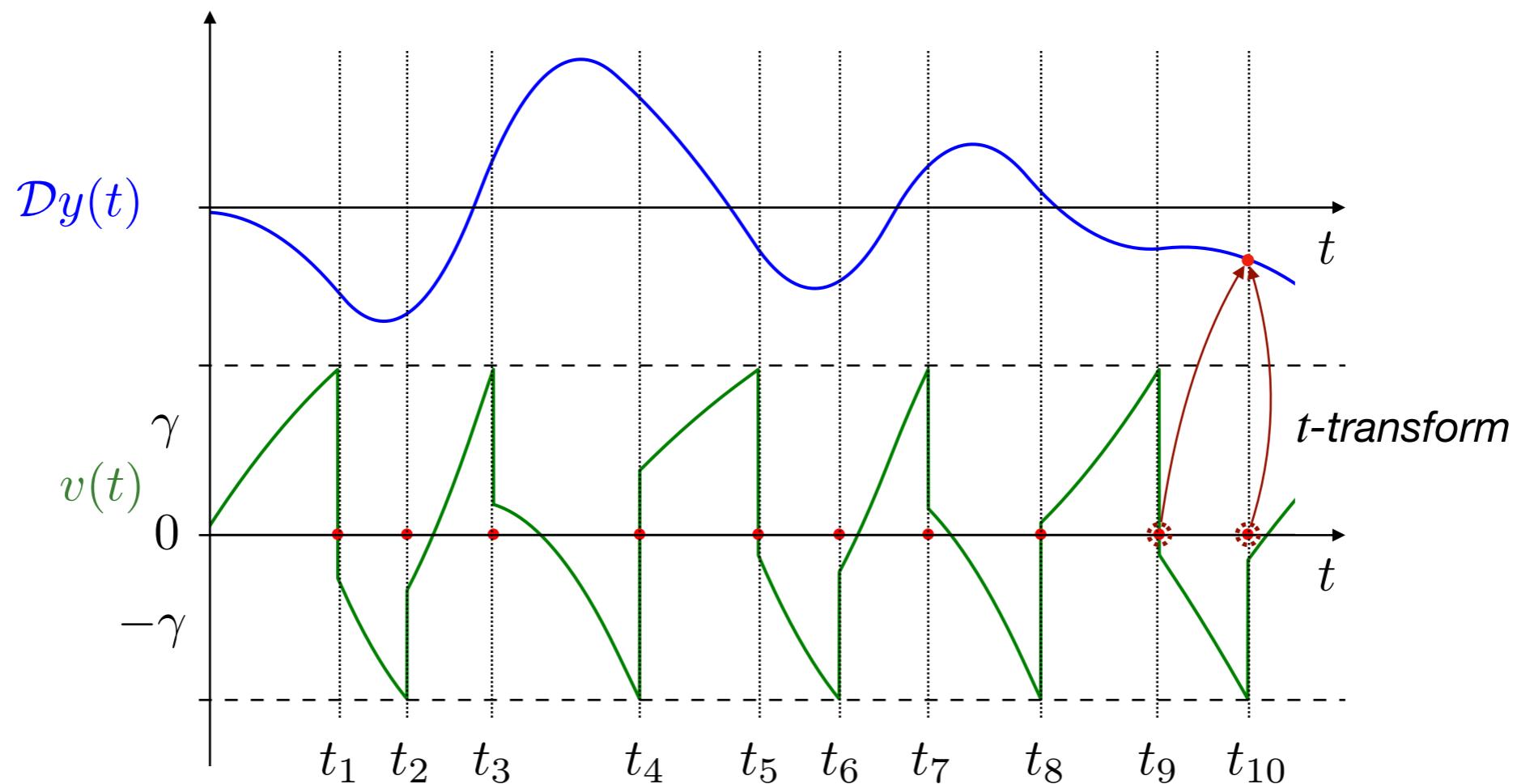


Fig 6: The *t*-transform gives the samples $\mathcal{D}y(t)$ using the trigger times

Differentiate-and-Fire Time-Encoding Machine

Corollary (*Stability*)

Let $y \in C^1(\mathbb{R})$ with $\|\mathcal{D}y\|_\infty \leq \beta$ be the input to the DIF-TEM with parameters $\{\alpha, \gamma\}$. The output $\mathcal{T}_{DF}y = \{t_n\}_{n \in \mathbb{Z}}$ satisfies

$$\frac{\gamma - \beta}{\alpha} \leq t_n - t_{n-1} \leq \frac{\gamma + \beta}{\alpha}.$$

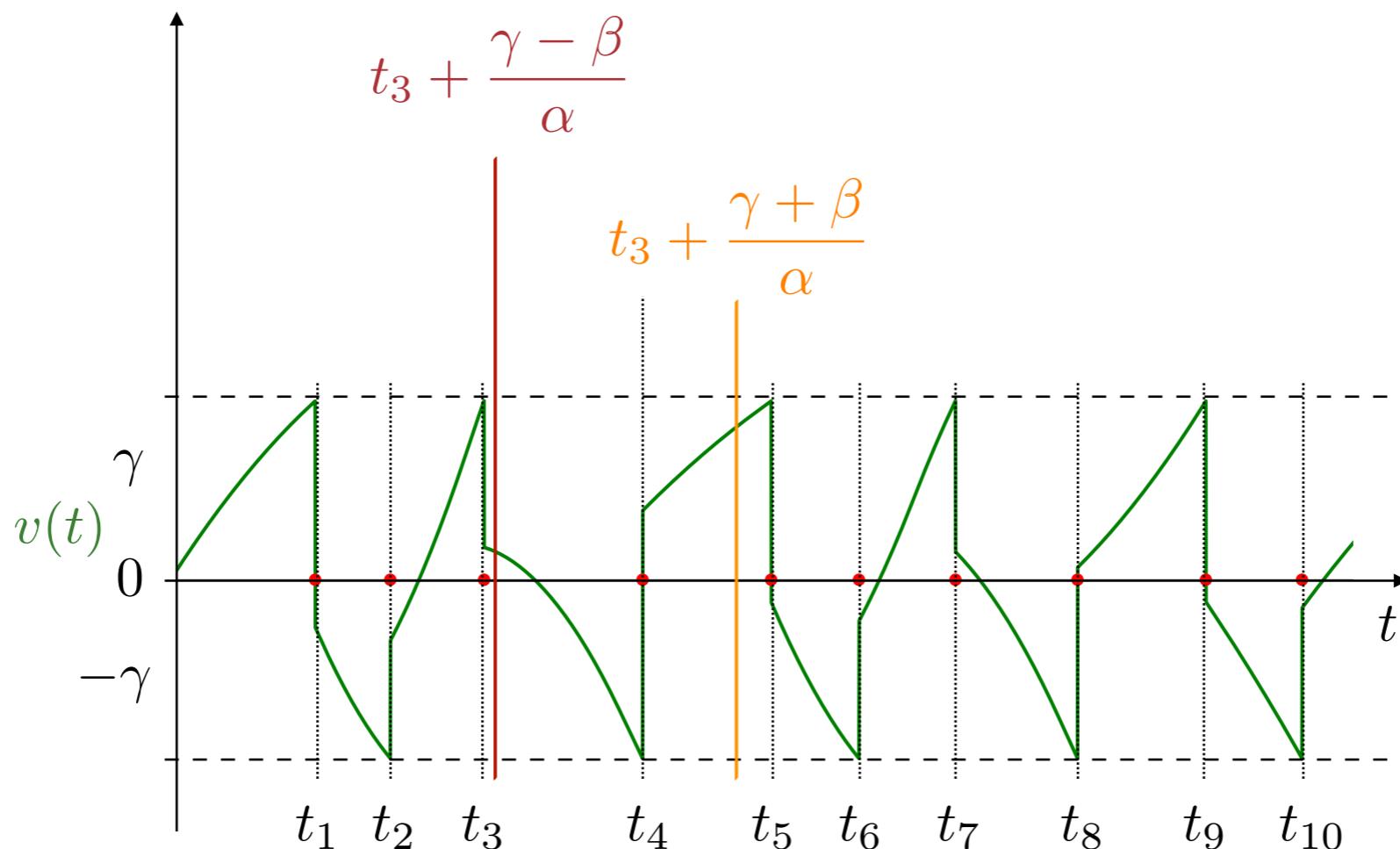


Fig 7: Stability ensures the existence of one trigger time in the interval $\left[t_n + \frac{\gamma - \beta}{\alpha}, t_n + \frac{\gamma + \beta}{\alpha}\right]$

Time-Encoding of FRI Signals

- Consider the T -periodic FRI signal $x \in L^2([0, T[)$

(Vetterli et al., '02)

$$x(t) = \sum_{m \in \mathbb{Z}} \sum_{k=0}^{K-1} c_k \varphi(t - \tau_k - mT)$$

- $\varphi \in L^2(\mathbb{R})$ is a known pulse
 - $\mathbf{c} = [c_0 \ c_1 \ \cdots \ c_{K-1}]^\top \in \mathbb{R}^K$ unknown amplitudes
 - $\boldsymbol{\tau} = [\tau_0 \ \tau_1 \ \cdots \ \tau_{K-1}]^\top \in \mathbb{R}^K$ unknown shifts
-
- Rate of innovation is $\frac{2K}{T}$
 - Fourier-series coefficients of $x \in L^2([0, T[)$

$$\hat{x}_m = \frac{1}{T} \hat{\varphi}(m\omega_0) \sum_{k=0}^{K-1} c_k e^{-j\omega_0 m \tau_k}; \quad \omega_0 = \frac{2\pi}{T}$$

Sum of Weighted
Complex Exponentials
(SWCE)

signal reconstruction \equiv parameter estimation

Prony's Annihilating Filter

- The *annihilating filter* $\mathbf{h} = (h_k)_{k=0}^K$ with roots $\vartheta_k = e^{-j\omega_0 \tau_k}$ (Prony, 1795)

$$H(z) = \sum_{k=0}^K h_k z^{-k} = h_0 \prod_{k=0}^{K-1} (1 - \vartheta_k z^{-1})$$

- Annihilation property*

$$(\mathbf{h} * \hat{\mathbf{x}})_m = \frac{1}{T} \sum_{k'=0}^{K-1} c_{k'} \vartheta_{k'}^m \underbrace{\sum_{k=0}^K h_k \vartheta_{k'}^{-k}}_{H(\vartheta_{k'})=0} = 0, \quad \forall m \in \mathbb{Z}$$

- Prony's method

$$\mathbf{X}\mathbf{h} = \mathbf{0}, \text{ i.e., } \mathbf{h} \in \text{null}(\mathbf{X})$$

- Roots of $\mathbf{h} \rightsquigarrow \tau$

Kernel-Based Time-Encoding

- Recovering $\hat{\mathbf{x}}$ from measurements of $x * g$

$$\begin{aligned} y(t) &= (x * g)(t) \\ &= \sum_{m \in \mathbb{Z}} \hat{x}_m \hat{g}(m\omega_0) e^{j\omega_0 mt} \end{aligned}$$

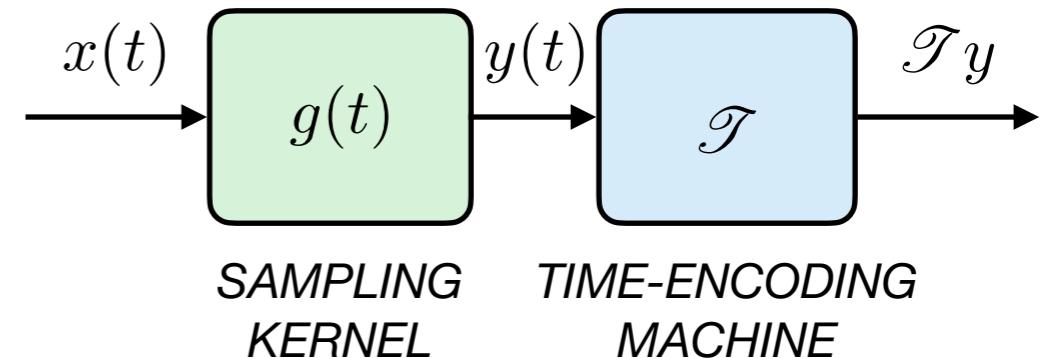


Fig 8: Kernel-based time-encoding of $x(t)$ using $g(t)$ as the sampling kernel

- Let g satisfy *alias-cancellation conditions*:

(Mulleti-CSS, '17)

$$\hat{g}(m\omega_0) = \begin{cases} g_m \neq 0, & m \in \llbracket -M, M \rrbracket \\ 0, & m \notin \llbracket -M, M \rrbracket \end{cases}$$

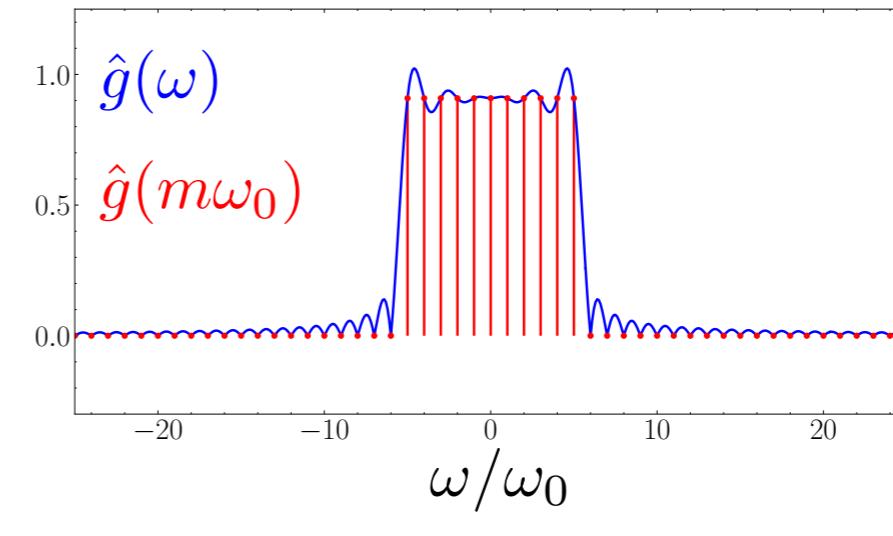
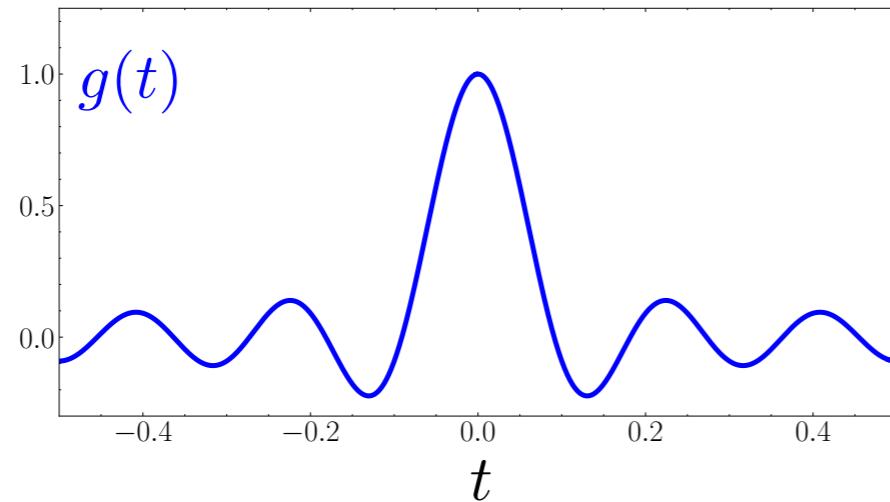


Fig 9: Fourier-domain sum-of-sincs (SoS) kernel: (a) time-domain; (b) Fourier-domain

Sufficient Conditions for Perfect Recovery

- $\mathcal{I}_{\text{DF}}y$ provides crossing-time instants of $\mathcal{D}y$

$$y_n \doteq (\mathcal{D}y)(t_n) = \sum_{m=-M}^M \hat{x}_m \cdot (\mathrm{j}\omega_0 m) \cdot e^{\mathrm{j}\omega_0 m t_n}$$

- L measurements in $[0, T[$, $\mathbf{y} = [y_1 \ \cdots \ y_L]^T$

$$\mathbf{y} = \mathbf{G}_{\text{DF}} \mathbf{S} \hat{\mathbf{x}}$$

where $\mathbf{S} = \text{diag}((\mathrm{j}\omega_0 m)_{m=-M}^M) \in \mathbb{C}^{N \times N}$ and

$$\mathbf{G}_{\text{DF}} = \begin{bmatrix} e^{-\mathrm{j}M\omega_0 t_1} & \dots & e^{-\mathrm{j}\omega_0 t_1} & 1 & e^{\mathrm{j}\omega_0 t_1} & \dots & e^{\mathrm{j}M\omega_0 t_1} \\ e^{-\mathrm{j}M\omega_0 t_2} & \dots & e^{-\mathrm{j}\omega_0 t_2} & 1 & e^{\mathrm{j}\omega_0 t_2} & \dots & e^{\mathrm{j}M\omega_0 t_2} \\ \vdots & & \vdots & \vdots & \vdots & & \vdots \\ e^{-\mathrm{j}M\omega_0 t_L} & \dots & e^{-\mathrm{j}\omega_0 t_L} & 1 & e^{\mathrm{j}\omega_0 t_L} & \dots & e^{\mathrm{j}M\omega_0 t_L} \end{bmatrix}$$

Lemma

The matrix \mathbf{G}_{DF} is left-invertible when $L \geq 2M + 1$

Sufficient Conditions for Perfect Recovery

- \mathbf{S} is singular
- \hat{x}_0 cannot be recovered
- We solve by setting $\hat{x}_0 = 0$ and $\mathbf{S}_{M+1,M+1} = 1$
- To get $L \geq 2K + 1$ time-instants in $[0, T]$

$$d(\mathcal{T}_{\text{DF}}y) < \frac{T}{L}$$

Proposition

Let the T -periodic FRI signal $x(t)$ be observed using a sampling kernel $g(t)$ that satisfies alias-cancellation conditions and a DIF-TEM with parameters $\alpha, \gamma > 0$. The time instants $\{t_n\}_{n=1}^L \subset \mathcal{T}_{\text{DF}} \cap [0, T[$ constitute a sufficient representation of x if $L \geq 2K + 1$ and the parameters of the DIF-TEM satisfy

$$\frac{\gamma + \|x * \mathcal{D}g\|_\infty}{\alpha} \leq \frac{T}{L}.$$

Simulation Results

- Consider the periodic FRI signal

$$x_1(t) = \sum_{m \in \mathbb{Z}} \sum_{k=0}^4 c_k \varphi(t - \tau_k - m)$$

- $\varphi(t) = \beta^{(3)}(10t)$
- Sampling kernel: SoS
- $\alpha = 16.4, \gamma = 2$

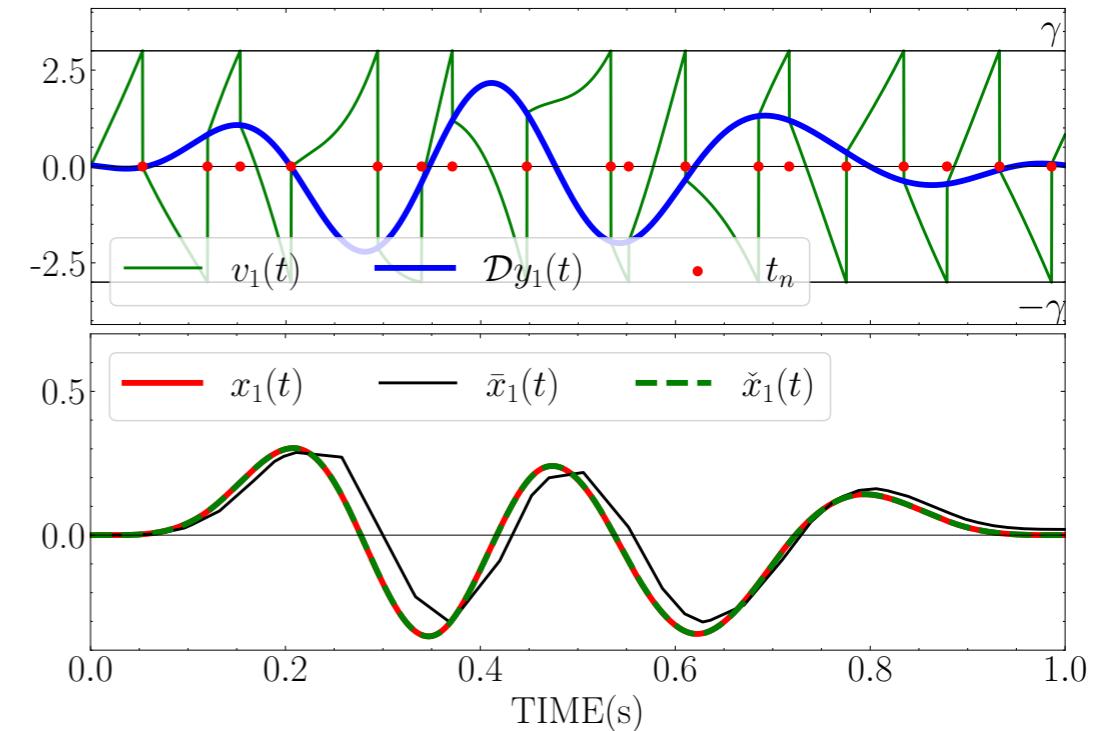


Fig 10: Time-encoding and reconstruction of $x_1(t)$:
 $\text{RSNR}(x_1, \dot{x}_1) = 51 \text{ dB}$; $\text{RSNR}(x_1, \bar{x}_1) = 9 \text{ dB}$

- Consider the periodic FRI signal

$$x_2(t) = \sum_{m \in \mathbb{Z}} \sum_{k=0}^4 c_k \delta(t - \tau_k - m)$$

- Sampling kernel: SoS
- $\alpha = 270, \gamma = 24.4$

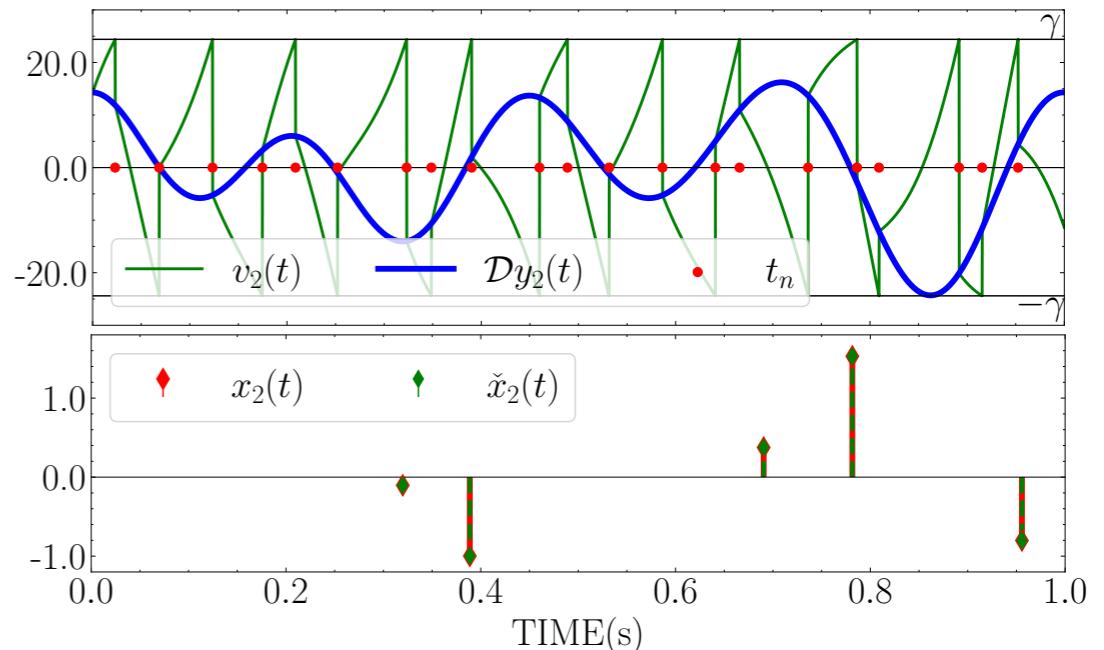


Fig 11: Time-encoding and reconstruction of $x_2(t)$:
Perfect reconstruction up to numerical precision

Summary and Conclusions

- We considered **differentiate-and-fire time-encoding** of FRI signals
- We proposed **kernel-based time-encoding** and analyzed sampling and reconstruction in the **Fourier-domain**
- We demonstrated that **perfect reconstruction** is possible using samples taken at the order of the rate-of-innovation of the signal

References

- [1] A. A. Lazar, “Time encoding with an integrate-and-fire neuron with a refractory period,” *Neurocomputing*, 2004.
- [2] A. J. Kamath, S. Rudresh, and C. S. Seelamantula, “Time encoding of finite-rate-of-innovation signals,” <https://arxiv.org/abs/2107.03344>, 2021.
- [3] G. R. de Prony, “Essai experimental et analytique: Sur les lois de la dilatabilité de fluides élastiques et sur celles de la force expansive de la vapeur de l’eau et de la vapeur de l’alcool, à différentes températures,” *J. de l’Ecole Polytechnique*, 1795.
- [4] M. Vetterli, P. Marziliano, and T. Blu, “Sampling signals with finite rate of innovation,” *IEEE Trans. Signal Process.*, June 2002.
- [5] S. Mulleti, and C. S. Seelamantula, “Paley–Wiener characterization of kernels for finite-rate-of-innovation sampling ,” *IEEE Trans. Signal Process.*, June 2017.
- [6] P. Martínez-Nuevo, S. Patil, and Y. Tsividis, “Derivative level-crossing sampling,” *IEEE Trans. Circuits Syst. II Express Briefs*, 2015.

Acknowledgements

- Prime Minister’s Research Fellowship
- Pratiksha Trust
- IISc. Institute of Eminence Funding (Government of India)

Thank You!

