Literature Review: Applying Non-Uniform Fast Fourier Transforms to Neuromorphic Data

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Abstract

Neuromorphic systems, which emulate biological neural networks to process data in an event-driven and sparse manner, present unique challenges for traditional signal processing techniques. Standard methods such as Fourier transforms, wavelets, and Hilbert transforms are often designed for continuous and regularly sampled data, making them less suitable for the irregular and sparse nature of neuromorphic signals. This paper reviews the current state of neuromorphic data processing methods and explores the potential of applying Non-Uniform Fast Fourier Transforms (NUFFTs) to address the challenges inherent in neuromorphic data analysis. The review highlights the limitations of traditional methods and introduces NUFFTs as an efficient technique for processing non-uniformly sampled data, preserving the signal's fidelity and resolution even in the presence of noise and sparsity. It is hypothesized that NUFFTs, while computationally more demanding, can provide more accurate feature extraction and better representations of underlying signal dynamics compared to conventional methods. Simulations will be conducted to investigate the performance of NUFFTs on clean and noisy neuromorphic data, and real-world neuromorphic data will be collected using a neuromorphic olfaction sensor to validate these findings. The results are expected to offer new insights into the advantages of NUFFTs for neuromorphic signal processing, potentially leading to improved methods for feature extraction, signal reconstruction, and analysis in neuromorphic systems.

Introduction

Neuromorphic data refers to information captured using neuromorphic hardware, which is designed to emulate the structure and function of biological neural systems and process all incoming information in a manner similar to the brain [1]. By mimicking neuron communication, neuromorphic systems generate data that is inherently sparse and event-driven. Only the moments when a sensor undergoes a significant change are recorded. Thus, unlike traditional computing, this event-driven nature allows neuromorphic systems to capture data with high temporal precision while reducing the amount of data needed for processing [1, 2].

Each event consists of two main components: the time-instant at which the signal's amplitude changes by a predefined threshold (the event time-instant), and the polarity of the change (event polarity) [3]. When first processing this data and extracting signal features, traditional signal processing methods such as Fourier transforms and clustering algorithms are commonly employed [4, 5, 6]. However, while these methods are efficient, one limitation is that they are typically designed for continuous, regularly sampled data. In contrast, neuromorphic data is sparse and irregular, prompting the need for novel approaches. Non-uniform sampling for Fourier-domain analysis is one such approach proposed as a potential solution, as this method may offer a more accurate representation of irregularly sampled signals. In addition, in recent years, significant research has focused on improving non-uniform Fourier transforms as a whole, resulting in algorithms that are faster, more efficient, and capable of handling complex data structures with greater accuracy [6]. Despite being computationally more demanding, non-uniform Fourier transforms account for the sparse nature of event-based signals, which holds promise for enhancing the analysis and interpretation of neuromorphic data. Moreover, no known research has yet implemented the specific non-uniform fast Fourier transform (NUFFT) for processing neuromorphic data.

Thus, this paper aims to provide a literature review of current techniques for processing neuromorphic data, leading to a discussion on the potential advantages and challenges of using NUFFTs. Furthermore, a hypothesis for the application of NUFFTs in neuromorphic data analysis will be proposed, and methods for simulating, testing, and validating this approach in future research will be outlined.

Literature Search Methodology

This work highlights recent papers from 2000 to 2025. The initial search process involved specifying a set of keywords, which were then used to search through multiple online libraries and academic databases, including Google Scholar, IEEE Xplore, and arXiv. The first primary search keywords used were "Neuromorphic" AND "signal processing", which returned roughly 28,000 results. To narrow down the search, the next primary keywords used in the search focused on specific methods, such as "Neuromorphic" AND "Fourier" and "Neuromorphic" AND "Wavelet". These searches returned roughly 14,000 and 5,000 results respectively, which were further filtered to include only primary research articles, excluding conference abstracts, opinions, and other non-peer-reviewed sources.

Further refinement was performed by searching for specific terms related to non-uniform Fourier transforms (NUFFT) in neuromorphic data. The keyword combination "Neuromorphic" AND "Non-uniform Fourier" returned only 2 results, which were both relevant to the area of NUFFTs but quite limited in direct applications to neuromorphic data. Yet, the search for "Neuromorphic" AND "NUFFT" yielded 13 results, some of which were also discovered to not pertain to neuromorphic data specifically. Altogether, this search process highlighted the current, conventional methods for processing neuromorphic data, as well as the gap in research utilizing NUFFTs in this field.

Inclusion criteria for the papers selected were as follows:

- **Publication Date**: Only papers published between 2000 and 2025 were considered to ensure that the review reflected the most up-to-date research.
- **Relevance**: Papers were selected based on their direct relevance to the intersection of neuromorphic computing and signal processing techniques, especially those involving NUFFT methods or related sparse signal processing techniques.
- **Methodological Approach**: Studies that presented clear methodologies for applying conventional processing techniques to neuromorphic data, as well as those that addressed theoretical, algorithmic, or experimental advancements, were prioritized.
- **Quality of Source**: Only peer-reviewed journals, conference papers, and articles were included.

Exclusion criteria for the papers selected were as follows:

- **Irrelevant Topics**: Papers unrelated to neuromorphic systems, signal processing for neuromorphic data, or non-uniform sampling techniques for neuromorphic signals were excluded, with the exception of examining the broader advancement of non-uniform Fourier transforms.

- **Non-peer-reviewed Work**: Papers that were not fully peer-reviewed or were in the form of abstracts, editorials, or opinion pieces were excluded to ensure the inclusion of only rigorous, validated research.
- **Duplicate Studies**: Articles presenting the same or highly similar content to already selected papers were excluded to avoid redundancy.

After applying these criteria, a total of 30 articles were selected for the final review. These articles together provided an overview of the advancements in neuromorphic data processing, in addition to a focus on novel developments of non-uniform Fourier transforms. Papers were chosen based on their contributions to the field, including theoretical frameworks, algorithm development, and practical applications. Each selected paper was analyzed for its contributions to understanding conventional methods for neuromorphic signal processing, how NUFFTs could be used to improve processing, and any limitations or challenges for both identified by the authors.

Conventional Neuromorphic Data Processing Methods

I. Fourier Transforms

Fourier transforms are by far the most traditional method for analyzing modern signals of any kind, and neuromorphic signals are no different. They are commonly used to convert time-domain signals into frequency-domain representations, providing valuable insight into the signal's frequency components. In the context of neuromorphic data, Discrete Fourier Transforms (DFTs) have been widely employed due to their ability to handle continuous signals effectively and their well-established theoretical foundations [4, 9, 10]. These transforms are particularly useful for applications requiring frequency analysis or spectral representation, such as noise filtering, signal compression, and feature extraction. Furthermore, extensive research has been done to accelerate these algorithms, resulting in the Fast Fourier Transform (FFT) and the Short-Time Fourier Transform (STFT), which have both been applied to neuromorphic data [8, 12, 13, 14]. Most notably, these algorithms are known for their efficiency and speed, making them attractive choices for real-time signal processing.

However, all of these traditional Fourier methods assume uniformly sampled data, which can be problematic for neuromorphic signals, which are sparse and event-driven. This misalignment can result in inaccuracies or inefficiencies when applying Fourier transforms directly to neuromorphic data. Specifically, the irregular and sparse nature of neuromorphic signals can result in significant challenges when attempting to represent them in a uniform frequency domain causing researchers to "insert missing samples between each real event" [4], experience a "loss of accuracy" [5, 7], or face difficulties in preserving the temporal resolution and fidelity of the original signal [13]. Consequently, several adaptations and complementary methods have been explored to better suit the characteristics of neuromorphic signals, such as wavelet transforms.

II. Wavelet Transforms

Wavelet transforms can handle non-stationary signals and provide more localized frequency information. Unlike Fourier transforms, which represent signals in terms of global frequency components, wavelet transforms allow for time-frequency analysis, enabling the detection of both low- and high-frequency features within specific time windows. This makes them particularly well-suited for neuromorphic signals, which often exhibit transient and irregular activity. Wavelet transforms are capable of preserving both the temporal and frequency characteristics of neuromorphic signals, making them less susceptible to the issues of misalignment and resolution loss seen with traditional Fourier methods. Several wavelet-based techniques, such as the Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT), have been investigated for neuromorphic data, with promising results in areas like event detection, spike train analysis, and anomaly detection [15, 16, 17, 18].

Despite their advantages, wavelet transforms also come with certain limitations. While wavelets are adept at handling non-stationary signals, they may still struggle with very sparse or highly irregular data, where the time-frequency resolution might not be as fine-grained as required [17]. The potential for overfitting when using wavelet transforms in combination with machine learning methods is another concern, especially in the presence of noisy data or attempting to scale these algorithms to more dynamic, uncontrolled environments [16].

III. Emerging Techniques

Other methods, including Hilbert transforms and sparse signal recovery techniques, have also been considered as alternatives to improve signal representation in neuromorphic systems [11, 19, 20]. Hilbert transforms are often used for extracting instantaneous frequency and phase information, making them effective for analyzing signals with rapidly changing frequencies or phase relationships. However, Hilbert transforms can be sensitive to noise, particularly in event-driven data with irregular intervals, which is common in neuromorphic systems. Small fluctuations in the data could significantly distort the phase and frequency estimates, affecting the reliability of the analysis [19].

Sparse signal recovery techniques in compressive sensing theory, on the other hand, aim to represent signals more efficiently by focusing on the most essential components, thus reducing the dimensionality of the data [23]. These techniques, which can be used in combination with transforms like wavelets or Fourier transforms, help identify and retain only the most significant features of a signal. In neuromorphic systems, sparse recovery techniques are beneficial because they allow for a more compact representation of the data, which is crucial for efficient processing in resource-constrained environments [21, 22]. Unlike traditional methods, sparse recovery does not require the entire signal to be processed in its entirety, but instead selects the important parts, leading to lower computational complexity and power consumption. However, while sparse recovery methods offer significant advantages in terms of efficiency, they can be sensitive to noise and may struggle with signals that are highly irregular or too sparse, which can limit their effectiveness in some neuromorphic applications [21, 22].

The Applicability of Non-Uniform Fast Fourier Transforms

The applicability of Non-Uniform Fast Fourier Transforms (NUFFTs) for processing neuromorphic data offers a promising solution to overcome some of the limitations posed by conventional methods. NUFFTs are specifically designed to handle non-uniformly sampled data, effectively addressing the irregular sampling intervals common in neuromorphic systems. The specific interpolations performed by NUFFTs—including time-domain interpolation, frequency-domain adjustments, signal reconstruction, and non-uniform frequency binning—help mitigate the challenges of sparsity and irregularity in neuromorphic data. These interpolations enable a more accurate and efficient representation of neuromorphic signals in the frequency domain, providing the potential for enhanced feature extraction, signal reconstruction, and overall analysis compared to traditional transforms. By preserving the temporal resolution and fidelity of the data, NUFFTs could significantly improve signal analysis, overcoming the shortcomings of conventional methods that often compromise these key aspects.

Outside of the field of neuromorphic computing, advancements to optimize the NUFFT have been made, further increasing its potential for practical use. Research has focused on improving the efficiency of NUFFT algorithms, reducing their computational complexity, and enabling their implementation on various hardware platforms, including GPUs and FPGAs [24, 25, 26, 27, 28, 29, 30]. These improvements may enable the adoption of NUFFTs for neuromorphic data processing, where both time and energy efficiency are critical.

However, the application of NUFFTs to neuromorphic data also presents certain challenges. First, although NUFFTs can handle non-uniform sampling, they may still struggle with highly irregular data, particularly if the signal lacks sufficient structure or contains a high degree of noise. Additionally, implementing NUFFTs on neuromorphic hardware could require significant adaptation of existing algorithms, as well as the development of specialized techniques to ensure efficient execution on spiking neural networks (SNNs). Another potential limitation is the computational cost of applying NUFFTs, which may be higher than other signal processing methods, particularly for larger datasets or more complex neuromorphic systems.

Despite these challenges, NUFFTs hold promise as a powerful tool for processing neuromorphic data, providing a more accurate and efficient alternative to traditional Fourier transforms. Future research will need to explore these challenges further, developing methods to optimize the application of NUFFTs for neuromorphic systems and testing their performance on real-world data.

Future Directions

Based on this literature review, the hypotheses for the proposed project of applying NUFFTs to real-world, neuromorphic data are as follows:

1) Despite having more computational cost, feature extraction for neuromorphic signals may be more accurate when utilizing NUFFTs and result in more precise representations of the underlying signal dynamics compared to conventional methods.
2) Simulations are expected to demonstrate that NUFFTs preserve the original signal's fidelity and resolution to a greater extent, particularly in the presence of noisy, highly sparse data.

To test these hypotheses, the following steps will be taken: first, simulated (clean and noisy) sparse signals will have a NUFFT applied in order to observe and derive precisely what occurs to neuromorphic data when a NUFFT is used. Then, real-world neuromorphic samples will be collected using a neuromorphic olfaction sensor. The sensor will be used to collect samples of various chemicals, gases, or substances, with careful consideration of how many and which substances should be included in the data set. Once the samples are collected, they will undergo processing using the NUFFT, and the results will be compared to those obtained from the standard FFT or other traditional signal processing methods.

A key challenge will be ensuring that the sensor captures enough data with high temporal resolution while avoiding overfitting or underfitting in the preprocessing stages. Furthermore, handling noise in real-world datasets will require robust noise filtering techniques. Validating the findings will involve comparing the performance of NUFFT-based processing with existing methods through various accuracy metrics, including signal reconstruction quality and feature extraction precision. The expected impact of these findings could lead to more efficient and accurate methods for processing neuromorphic data, with implications for real-time applications in areas such as sensory processing and pattern recognition.

References

[1] Schuman, C. D., Potok, T. E., Patton, R. M., Birdwell, J. D., Dean, M. E., Rose, G. S., & Plank, J. S. A survey of neuromorphic computing and neural networks in hardware. *arXiv*. 2017.
[2] Kudithipudi, D., Schuman, C., Vineyard, C.M. *et al.* Neuromorphic computing at scale. *Nature.* 2025; 637: 801–812.
[3] Kamath, A. J., & Seelamantula, & C. S. Neuromorphic sampling of sparse signals. *arXiv.* 2023.
[4] Grundmark, J., Hamrell, H., Berneland, J., & Gustafsson, D., Frequency analysis on neuromorphic data using discrete fourier transform. *Twelfth International Conference on Image Processing Theory, Tools and Applications (IPTA)*. 2023; 1-6.
[5] Sabatier, Q., Ieng, S. H., & Benosman, R. Asynchronous event-based Fourier analysis. *IEEE Transactions on Image Processing*. 2017; 26(5): 2192-2202.
[6] Xiang, S., Zhang, T., Han, Y., Guo, X., Zhang, Y., & Shi, Y. Neuromorphic speech recognition with photonic convolutional spiking neural networks. *IEEE Journal of Selected Topics in Quantum Electronics.* 2023; 29(6).
[7] López-Randulfe, J., Reeb, N., Karimi, N., Liu, C., Gonzalez, H. A., Dietrich, R., Vogginger, B., Mayr, C., & Knoll, A. Time-coded spiking Fourier transform in neuromorphic hardware. *arXiv.* 2022.
[8] Orchard, G., Frady, E. P., Rubin, D. B. D., Sanborn, S., Shrestha, S. B., & Somme, F. T. Efficient neuromorphic signal processing with Loihi 2. *IEEE Workshop on Signal Processing Systems (SiPS)*. 2021; 254-259.
[9] Galicia, M., Happek, L., Balzer, M., & Leupers, R.. Frequency and noise characterization for baseband signal processing on neuromorphic circuits. *21st IEEE Interregional NEWCAS Conference (NEWCAS)*. 2023; 1-5.
[10] Arsalan, M., Santra, A., & Issakov, V. Power-efficient gesture sensing for edge devices: mimicking fourier transforms with spiking neural networks. *Appl Intell.* 2023; 53: 15147–15162.
[11] Zhangm, L., Yang, Z., Aras, K., Efimov, IR., & Adam GC. Discrete Hilbert transform via memristor crossbars for compact biosignal processing. *IEEE 16th International Conference on Application of Information and Communication Technologies (AICT)*. 2022; 1-5.
[12] Lee, JE., Lee, CJ., Lee, DS., Kim, DW., & Seo, YH. Optimization of deep neural network for neuromorphic system. *34th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC).* 2019; 1-2.
[13] Alsakkal, MA. & Wijekoon, J. Spiketrum: an FPGA-based implementation of a neuromorphic cochlea. *IEEE Transactions on Circuits and Systems I: Regular Papers*. 2025; 1-9.
[14] Chen, P., Xiong, X., Zhang, B., Ye, Y., Pan, G., & Lin, P. Neuromorphic auditory classification based on a single dynamical electrochemical memristor. *Neuromorphic Computing and Engineering*. 2024; 4(1).
[15] Fang, Y., Wang, Z., Zhang, L., Cao, J., Chen, H., & Xu, R. Spiking wavelet transformer. *In: Leonardis, A., Ricci, E., Roth, S., Russakovsky, O., Sattler, T., Varol, G. (eds) Computer Vision – ECCV.* 2024.
[16] Surovich, M., Shrestha, S., Douard, N., Giakos, Z., & Giakos, G. Dynamic segmentation using a novel neuromorphic polarimetric imaging system. *IEEE International Conference on Imaging Systems and Techniques (IST)*. 2017; 1-6.
[17] Wang, Z., Guo, L., & Adjouadi, M. Wavelet decomposition and phase encoding of temporal signals using spiking neurons. *Neurocomputing.* 2016; 173(Part 3): 1203-1210.
[18] Chen, DR. & Wong, YC. Neuromorphic solutions: digital implementation of bio-inspired spiking neural network for electrocardiogram classification. *Indonesian Journal of Electrical Engineering and Computer Science.* 2022; 27(1):528-537.
[19] Haghighatshoar, S., & Muir, D. R. Low-power SNN-based audio source localisation using a Hilbert Transform spike encoding scheme. *Communications Engineering.* 2025; 4(18).
[20] A. Henderson *et al*. Spiking neural networks for LPI radar waveform recognition with neuromorphic computing. *IEEE Radar Conference (RadarConf23)*. 2023; 1-6.
[21] Zhang,X., Yu, L., Zheng, G., & Eldar, YC. Spiking sparse recovery with non-convex penalties. *IEEE Transactions on Signal Processing*. 2022; 70:6272-6285.
[22] Han, X., He, X., & Ju, X. A distributed neurodynamic algorithm for sparse signal reconstruction via ℓ_1-minimization. *Neurocomputing.* 2023; 550(14).

[23] Ahmed, I., Khalil, A., Ahmed, I., & Frnda, J. Sparse signal representation, sampling, and recovery in compressive sensing frameworks. *IEEE Access*. 2022; 10: 85002-85018.
[24] Greengard, L. & Lee, J. Accelerating the Nonuniform fast Fourier transform. *Society for Applied and Industrial Mathematics.* 2004; 46(3): 443-454.
[25] Wen, M. & Houlihan, J. Application of the nonuniform fast Fourier transform to non-uniformly sampled Fourier transform spectrometers. *Optics Communications.* 2023; 540.
[26] Zhang, K. & Kang, JU. Graphics processing unit accelerated non-uniform fast Fourier transform for ultrahigh-speed, real-time Fourier-domain OCT. *Opt. Express.* 2010; 18(22): 23472-23487.
[27] Wei, D. & Yang, J. Non-uniform sparse Fourier transform and its applications. *IEEE Transactions on Signal Processing*. 2022; 70: 4468-4482.
[28] Kestur, S., Park, S., Irick, KM., & Narayanan, V. Accelerating the nonuniform fast Fourier transform using FPGAs. *18th IEEE Annual International Symposium on Field-Programmable Custom Computing Machines*. 2010:19-26.
[29] Fessler, JA. On NUFFT-based gridding for non-Cartesian MRI. *Journal of Magnetic Resonance.* 2007; 188(2): 191-195.
[30] Jacob, M. Optimized non-uniform fast Fourier transform (NUFFT) for iterative tomographic reconstruction. *IEEE International Conference on Acoustics, Speech and Signal Processing*. 2009: 673-676.