



## Fast and Accurate Partial Fourier Transform for Time Series Data

#### Yong-chan Park, Jun-Gi Jang, and U Kang

#### Computer Science & Engineering Seoul National University







### Introduction

- Existing Works
- Proposed Method
- Experiments
- Conclusion





## **Fourier Transform**

- Fundamental tool for numerous applications
  - Signal / image processing
  - Data compression (e.g., mp3 and jpg)
  - Medical imaging (e.g., MRI)
  - Anomaly detection



https://www.gettyimages.com https://www.pinclipart.com https://www.kissclipart.com https://commons.wikimedia.org





### **Fourier Transform**

- Temporal or spatial domain  $\rightarrow$  Frequency domain



Spatial domain

Frequency domain





## **Fourier Transform**

- Strong energy compaction or sparsity
  - Fourier coefficients are mostly small or equal to zero



Spatial domain

Frequency domain







- Fast Fourier Transform (FFT) is inefficient
  - FFT always computes *all* the coefficients



## Most of the coefficients are just discarded!







- FFT computes even the unnecessary coefficients
  - Is it possible to efficiently compute only a few of them?



How can we do this directly?





## **Problem Definition**

- Partial Fourier Transform
  - Given
    - Complex-valued vector *a* of size *N*
    - Non-negative integer  $M \ll N$
    - Integer  $\mu$
  - Estimate
    - Fourier coefficients of a for  $[\mu M, \mu + M]$



### Outline



- Introduction
- Existing Works
- Proposed Method
- Experiments
- Conclusion







- Fast Fourier Transform (FFT) rapidly computes the full Fourier coefficients
  - FFT has been highly optimized over decades
  - Time complexity:  $O(N \log N)$

- No option to efficiently compute only a few coefficients
- Unnecessary coefficients are just discarded





## **Goertzel Algorithm**

- Goertzel algorithm is one of the first methods for computing partial Fourier coefficients
  - Time complexity: *O*(*MN*)

- Essentially the same as computing individual coefficients
- It is limited to rare scenarios where a very few number of coefficients are required







- Subband DFT decomposes the input into a set of subsequences, and removes some of them with small energy contribution
  - Time complexity:  $O(N + M \log N)$

- Substantial issue of low accuracy
- No option to set an error bound







- FFT Pruning is a modification of the standard split-radix FFT
  - Almost optimized because it uses FFT as a subroutine
  - Time complexity:  $O(N \log M)$

- The performance gains are rather modest in practice
- PFT (proposed) significantly outperforms Pruned FFT



### Outline



- Introduction
- Existing Works
- Proposed Method
- Experiments
- Conclusion







### PFT (Partial Fourier Transform)

- Efficiently computes a part of Fourier coefficients
- Time complexity:  $O(N + M \log M)$  (state-of-the-art)
- Provides an option to set an arbitrary numerical precision
- Main ideas
  - Polynomial approximation
  - Base exponential function
  - Reordering operators





## **Polynomial Approximation**

- PFT approximates a set of smooth twiddle factors by polynomials
  - Significantly reduces the computational cost due to the mixture of many twiddle factors = trigonometric functions
  - Typically, a smoother function results in a better polynomial approximation





## **Polynomial Approximation**

- a: complex-valued array of size N
- $\widehat{a}$ : Fourier transform of a
- $[N] = \{0, 1, \dots, N 1\}$  $N = pq \ (p, q > 1)$

 $\omega_N = e^{-2\pi i/N}$ 







- *a*: complex-valued array of size *N*
- $\widehat{a}$ : Fourier transform of a
- $[N] = \{0, 1, ..., N 1\}$  $N = pq \ (p, q > 1)$  $\omega_N = e^{-2\pi i/N}$



However, approximating all the factors is time-consuming





- Fix a **base exponential function** and exploit the laws of exponents:  $e^{ab} = (e^a)^b$ 
  - All data-independent factors can be precomputed
  - Bypasses the approximation problem





- $||f||_A = \sup\{|f(x)| : x \in A\}$
- $P_{\alpha}$ : set of polynomials of degree at most  $\alpha$

 $\xi, u \in \mathbb{R}$ 

- $\epsilon$ : tolerance
- r: number of approximation terms

$$\mathcal{P}_{\alpha,\xi,u} \coloneqq \underset{P \in P_{\alpha}}{\operatorname{arg\,min}} \|P(x) - e^{uix}\|_{|x| \le |\xi|}$$
$$\xi(\epsilon, r) \coloneqq \sup\{\xi \ge 0 : \|\mathcal{P}_{r-1,\xi,\pi}(x) - e^{\pi ix}\|_{|x| \le \xi} \le \epsilon\}$$
$$\mathsf{We\ use\ this\ as\ a\ base}$$





## **Base Exponential Function**

• If  $\xi(\epsilon, r) \ge M/p$ , the following holds for  $|m| \le M$ :



#### We approximate only the base, and re-scale the polynomial





## **General Target Range**

- A slight modification of the algorithm allows the target range to be arbitrarily centered at  $\mu \in \mathbb{Z}$ 

$$m \in [\mu - M, \mu + M]$$

$$A = (a_{k,l}) = a_{qk+l}$$

$$B = (b_{l,j}) = \omega_N^{\mu(l-q/2)} w_{\epsilon,r,j} (1 - 2l/q)^j$$

$$w_{\epsilon,r,j} : j^{th} \text{ coefficient of } \mathcal{P}_{r-1,\xi(\epsilon,r),\pi}$$

$$\hat{a}_m \sim \omega_{2p}^m \sum_{j \in [r]} ((m-\mu)/p)^j \sum_{k \in [p]} \omega_p^{mk} \sum_{l \in [q]} a_{k,l} b_{l,j}$$





## **Reordering operators**

- Reordering operators results in a significant computational benefit
  - Achieve the lowest time complexity  $O(N + M \log M)$



#### **Dot Products**



### Outline



- Introduction
- Existing Works
- Proposed Method
- Experiments
- Conclusion





## **Experimental Setup**

• We use both synthetic and real-world datasets

Dataset	Туре	# of Time Series	Length
$\{S_n\}_{n=12}^{22}$	Synthetic	1000	2 <sup>n</sup>
Urban Sound	Real-world	4347	32000
Air Condition	Real-world	29	19735
Stock	Real-world	4	1012

- Measure: relative  $\ell_2$  error
  - We use single-precision floating-point format, and set the relative  $\ell_2$  error to be less than  $10^{-6}$







- PFT shows state-of-the-art speed on all the datasets *without* sacrificing accuracy
  - Even when N is not a power of 2 or has a large prime







## Precision vs. Speed

- PFT can set an arbitrary numerical precision
  - The trade-off is very useful when the fast evaluation is of utmost importance

$(N = 2^{-2})$					
	Precision				
M	$10^{-6}$	$10^{-4}$	$10^{-2}$		
29	1.273	1.249 (.98)	1.238 (.97)		
$2^{10}$	1.295	1.278 (.99)	1.244 (.96)		
$2^{11}$	1.332	1.293 (.97)	1.251 (.94)		
$2^{12}$	1.491	1.329 (.89)	1.277 (.86)		
$2^{13}$	1.526	1.400 (.92)	1.343 (.88)		
$2^{14}$	1.692	1.607 (.95)	1.512 (.89)		
$2^{15}$	1.940	1.872 (.96)	1.740 (.90)		
$2^{16}$	2.821	2.469 (.88)	2.297 (.81)		
$2^{17}$	5.411	4.590 (.85)	4.058 (.75)		
$2^{18}$	11.924	9.927 (.83)	8.733 (.73)		

n221



# **Anomaly Detection (1)**

22

- PFT successfully detects the anomalies, regardless of different patterns of data
  - The outliers found by PFT exactly coincide with those by FFT











## **Anomaly Detection (2)**

- PFT results in interpretable anomaly detections
  - Stock prices of Facebook, Amazon, Netflix, and Google
  - Each outlier is closely related to a real-world event





### Outline



- Introduction
- Existing Works
- Proposed Method
- Experiments
- Conclusion







### PFT (Partial Fourier Transform)

- Efficiently computes a part of Fourier coefficients
- Main ideas of PFT
  - Polynomial approximation of smooth twiddle factors
  - Base exponential function for precomputation
  - Reordering operators
- Experimental results
  - PFT shows state-of-the-art speed without accuracy loss





# Thank you!

https://github.com/snudatalab/PFT