RawAlign

Accurate, Fast, and Scalable Raw Nanopore Signal Mapping via Combining Seeding and Alignment

Joël Lindegger

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Nanopore Sequencing

Nanopore Sequencing: a widely used sequencing technology

- Can sequence large fragments of nucleic acid molecules (up to >2Mbp)
- Offers high throughput
- Cost-effective

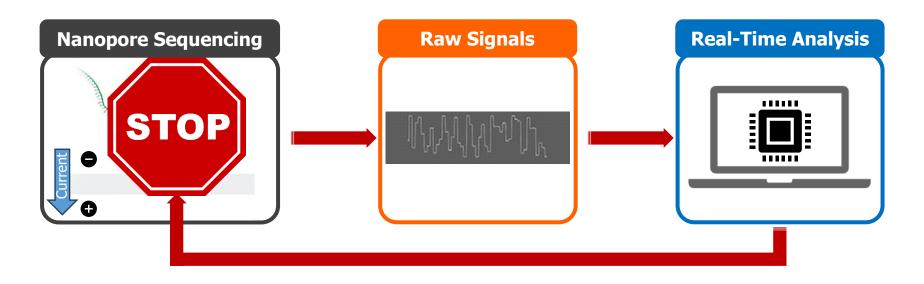
Enables real-time genome analysis







Real-Time Analysis with Nanopore Sequencing



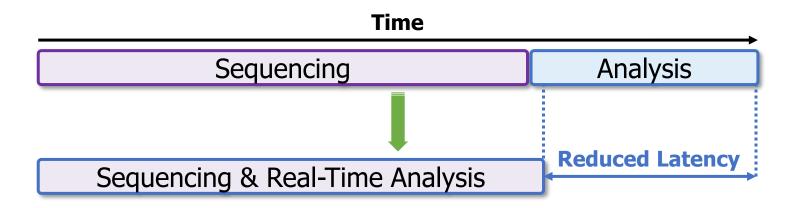
Raw Signals: Ionic current measurements generated at a certain throughput

Real-Time Analysis: Analyzing all raw signals by matching the throughput

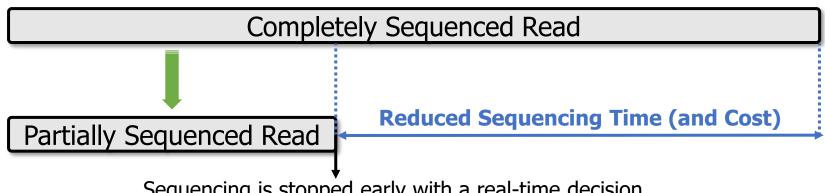
Real-Time Decisions: Stopping sequencing early based on real-time analysis

Benefits of Real-Time Genome Analysis

Reducing latency by overlapping the sequencing and analysis steps



Reducing sequencing time and cost by stopping sequencing early



Sequencing is stopped early with a real-time decision

Challenges in Real-Time Genome Analysis

Rapid analysis to match the nanopore sequencer throughput

Timely decisions to stop sequencing as early as possible

Accurate analysis from noisy raw signal data

Power-efficient computation for scalability and portability

Executive Summary

Problem: Real-time analysis of nanopore raw signals **fails to scale** to large reference databases (e.g., the human genome)

Goal: Analyze raw nanopore signals with

- high accuracy
- high throughput
- low latency
- low memory usage
- needing few bases to be sequenced

for a wide range of reference database size

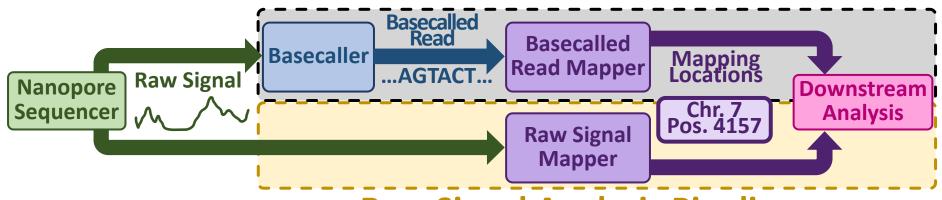
RawAlign: The **first Seed-Filter-Align mapper** for raw nanopore signals

Key Results:

- Only tool to map raw nanopore signals to large reference databases with high accuracy
- Generalizes to all kinds of reference database sizes
- Compared to **RawHash**: **similar throughput** (between $0.80 \times -1.08 \times$) while **improving accuracy** on all datasets (between $1.02 \times -1.64 \times$ F-1 score)

Nanopore Signal Analysis Overview

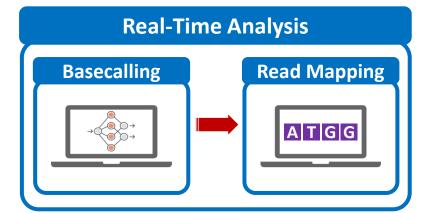
Conventional Analysis Pipeline



Raw Signal Analysis Pipeline

Existing Solutions Nanopore Signal Analysis

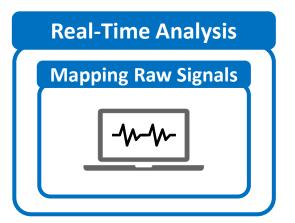
1. Deep neural networks (**DNNs**) for translating **signals** to **bases**



Less noisy analysis from basecalled sequences

Costly and power-hungry computational requirements

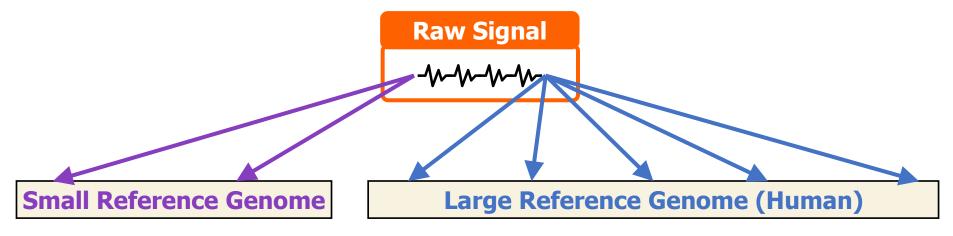
Mapping signals to reference genomes without basecalling



Raw signals contain richer information than bases

Efficient analysis with better scalability and portability

The Problem - Mapping Raw Signals



Fewer candidate regions in **small genomes**

Substantially **larger number of regions** to check **per read** as the genome size increases

Accurate mapping

Problem: Probabilistic mechanisms on many regions → inaccurate mapping

High throughput

Problem: Distance calculation on many regions → reduced throughput

The Problem - Mapping Raw Signals

Raw Signal

Existing solutions are inaccurate or inefficient for large genomes

Accurate mapping

on many regions -> inaccurate mapping

High throughput

on many regions -> reduced throughput

Outline

Background

RawAlign

Evaluation

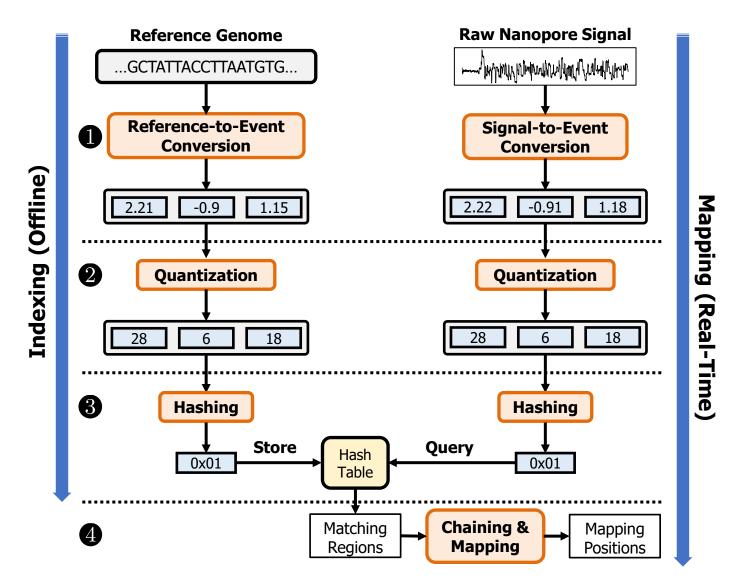
Conclusion

Goal

Analyze raw nanopore signals with

- high accuracy
- high throughput
- low latency
- low memory usage
- needing few bases to be sequenced for a wide range of reference database size

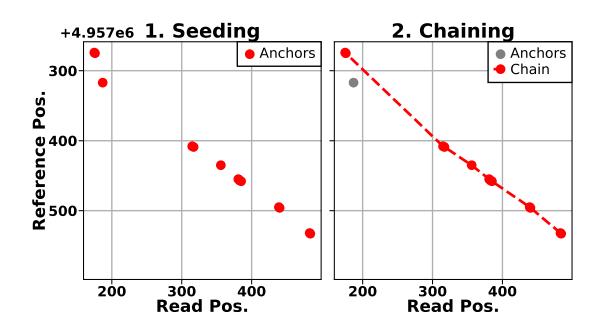
RawHash Overview [Firtina+]





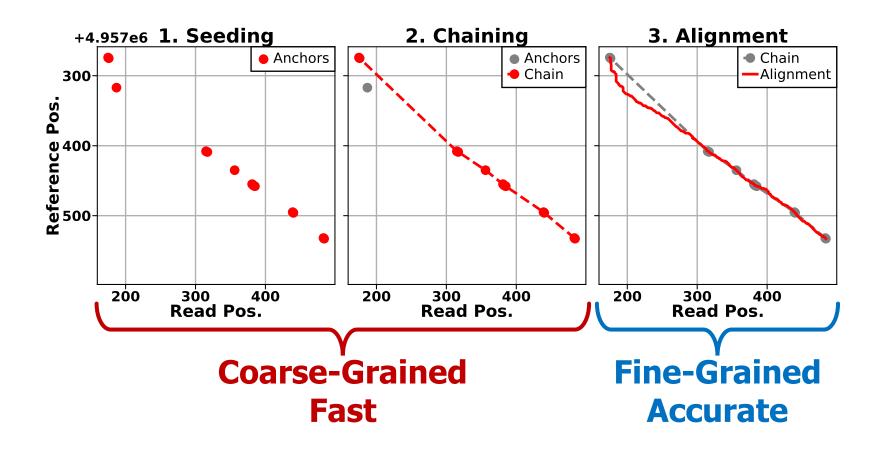
Firtina+, "RawHash: Enabling Fast and Accurate Real-Time Analysis of Raw Nanopore Signals for Large Genomes", Bioinformatics, 2023

RawHash Overview [Firtina+]

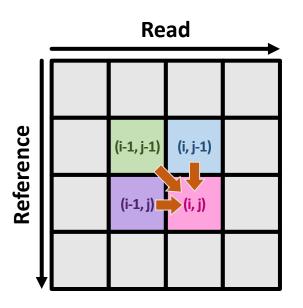




RawAlign Overview



Alignment Algorithms



```
Needleman-Wunsch Compare Basecalled Sequences dp[i,j] = min - dp[i-1,j-1] + (read[i] == ref[j]) ? 0:1 dp[i-1,j] + 1 dp[i-1,j-1] + 1
```

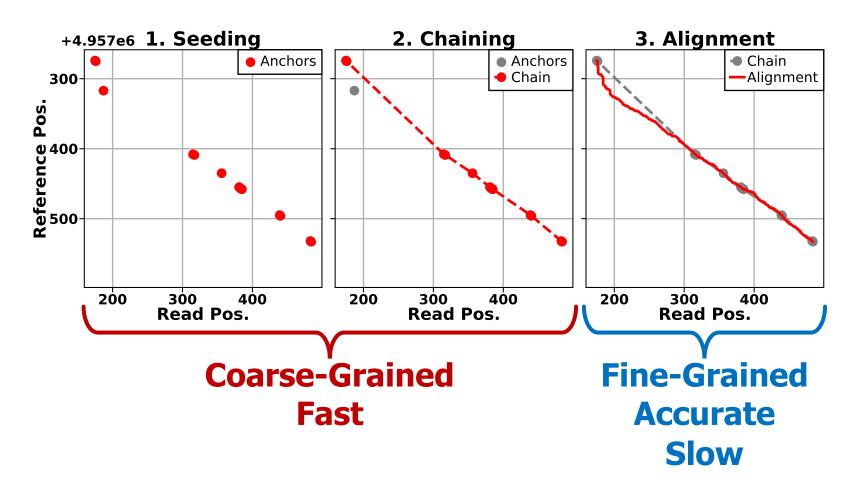
```
Dynamic Time Warping Compare Raw Signal Sequences dp[i,j] = min - dp[i-1,j-1] \\ dp[i-1,j] + abs(read[i] - ref[j]i)dp[i-1,j-1]
```

Challenges in Integrating Alignment to Mapping

1. Alignment Algorithms Called Frequently

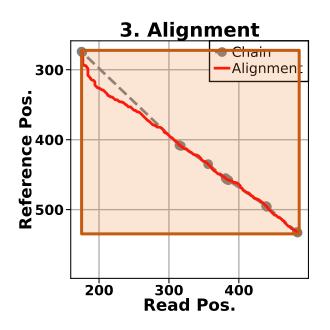
2. Each Call to Alignment Algorithm is Expensive

Recall: RawAlign Overview





Alignment is Expensive



Dynamic programming table scales with the **square** of the **read length**

Efficient Alignment

RawAlign efficiently integrates alignment through

- Pre-alignment filtering (chaining)
- 2. Early termination (branch-and-bound)
- 3. Anchor-guided alignment
- 4. Banding/windowing
- Vectorization (SIMD)

More in The Paper

RawAlign efficiently integrates alignment through

- Pre-alignment filtering (chaining)
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All Details in the Paper

RawAlign: Accurate, Fast, and Scalable Raw Nanopore Signal Mapping via Combining Seeding and Alignment

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Evaluation Methodology

- Compared to UNCALLED [Kovaka+, Nat. Biotech. 2021] Sigmap [Zhang+, ISMB/ECCB 2021] and RawHash [Firtina+, Bioinformatics 2023]
 - CPU baseline: Intel Xeon Gold 6226R @2.9GHz
 - **64 threads** for each tool

- Use cases for real-time genome analysis:
 - 1. Read mapping
 - 2. Relative abundance estimation
 - 3. Contamination analysis

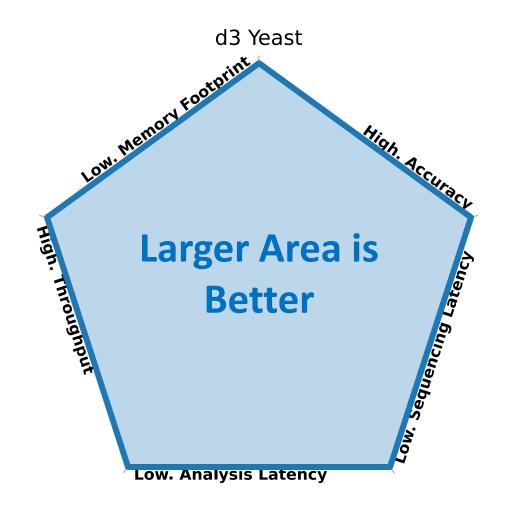
Evaluation Methodology

- Evaluation metrics:
 - Memory footprint (GB)
 - Mean throughput (bp/s) per thread
 - Mean analysis latency (ms)
 - Mean **sequencing latency (chunks)**
 - Accuracy (F-1 score)

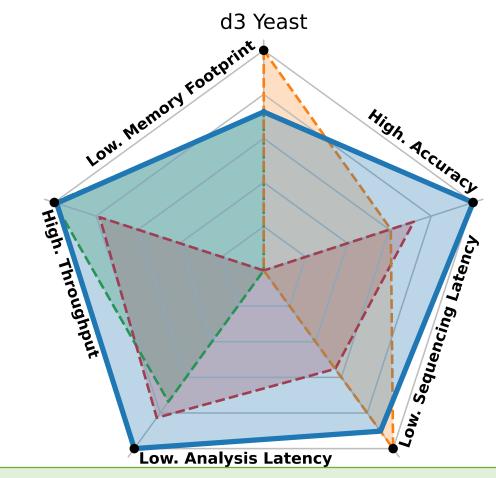
Datasets:

	Organism	Flow Cell Version	Reads (#)	Bases (#)	SRA Accession	Reference Genome	Genome Size	
Read Mapping								
d1	SARS-CoV-2	R9.4	1,382,016	594M	CADDE Centre	GCF_009858895.2	29,903	
d2	E. coli	R9.4	353,317	2,364M	ERR9127551	GCA_000007445.1	5M	
d3	Yeast	R9.4	49,992	380M	SRR8648503	GCA_000146045.2	12M	
d4	Green Algae	R9.4	63,215	1,335M	ERR3237140	GCF_000002595.2	111M	
d5	Human HG001	R9.4	269,507	1,584M	FAB42260 Nanopore WGS	T2T-CHM13 (v2)	3,117M	
			Rela	ative Abur	ndance Estimation			
	D1-D5		2,118,047	6,257M	d1-d5	d1-d5	3,246M	
				Contamin	ation Analysis			
	D1 and D5		1,651,523	2,178M	d1 and d5	d1	29,903	









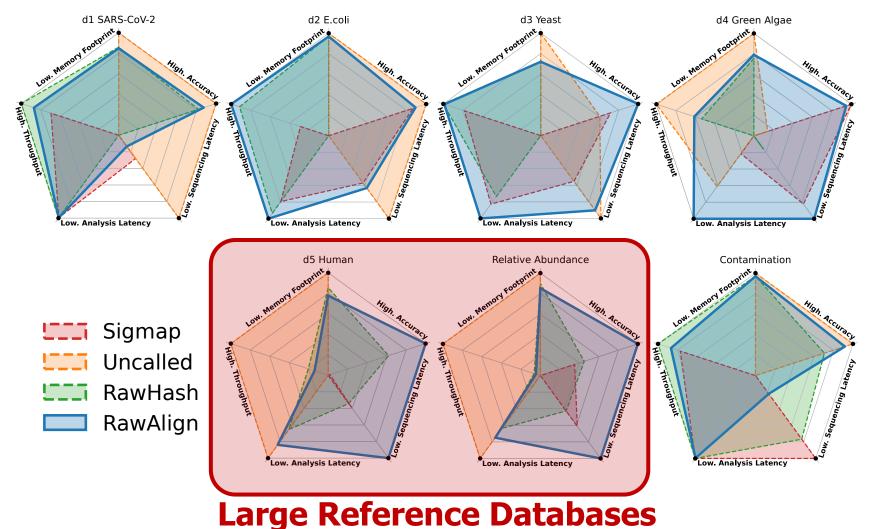
RawAlign is the **only tool** to do **well in all metrics** and has the **highest accuracy and throughput**

Sigmap

Uncalled

RawHash

RawAlign



"Difficult" Datasets

	Memory	Throughput	Analysis	Sequencing	Accuracy
d1 SARS-CoV-2		(bp/s)		Latency (Chunks)	(F-1)
Uncalled	0.280	6,575.310	29.244	0.410	0.972
Sigmap	28.250	350,565.180	1.111	1.005	0.711
RawHash	4.210	502,043.190	0.942	1.238	0.925
RawAlign	4.520	438,089.990	1.070	1.126	0.939
d2 E.coli					
Uncalled	0.800	5,174.050	115.787	1.290	0.973
Sigmap	111.170	19,215.930	34.441	2.111	0.967
RawHash	4.270	49,559.740	19.754	3.200	0.928
RawAlign	0.000	53,693.170	13.323	1.995	0.968
d3 Yeast					
Uncalled	0.580	5,151.670	159.304	2.773	0.941
Sigmap	14.710	15,217.010	67.602	4.139	0.947
RawHash	4.530	17,996.930	77.586	5.826	0.906
RawAlign	4.530	17,854.670	48.394	3.071	0.963
d4 Green Algae					
Uncalled	1.260	8,174.320	440.815	11.790	0.840
Sigmap	53.710	2,251.370	608.898	5.804	0.938
RawHash	14.060	5,429.580	700.304	10.646	0.824
RawAlign	12.200	5,871.450	276.094	4.514	0.932
d5 Human					
Uncalled	13.170	5,612.920	1,077.536	12.959	0.320
Sigmap	313.400	195.180	16,296.435	10.401	0.327
RawHash	56.940	1,298.520	6,318.984	10.695	0.557
RawAlign	80.350	956.310	3,510.682	6.321	0.703
Contamination					
Uncalled	1.060	6,607.850	199.283	3.557	0.964
Sigmap	111.650	405,956.490	1.206	2.062	0.650
RawHash	4.280	524,042.570	1.139	2.409	0.872
RawAlign	4.500	455,376.380	2.004	3.227	0.938
Relative Abunda	nce				
Uncalled	10.870	6,721.770	309.079	4.921	0.218
Sigmap	506.340	181.880	5,670.365	3.338	0.406
RawHash	60.760	596.740	2,264.014	3.816	0.459
RawAlign	83.760	480.050	1,652.162	2.336	0.754



Relative Abundance Results

Tool	SARS-CoV-2	E.coli	Yeast	Green Algae	Human	Distance	-
Ground Truth	0.652	0.167	0.024	0.030	0.127		State-of-the-art
minimap2	0.613	0.163	0.025	0.053	0.147	0.050	basecalling baseline
Uncalled	0.072	0.466	0.001	0.150	0.312	0.689	3
Sigmap	0.201	0.446	0.002	0.123	0.229	0.549	
RawHash	0.309	0.440	0.000	0.073	0.178	0.445	
RawAlign	0.565	0.248	0.002	0.050	0.136	0.123	RawAlign

RawAlign approaches the accuracy of the state-of-the-art basecalling-based analysis pipeline (using minimap2)



All Details in the Paper

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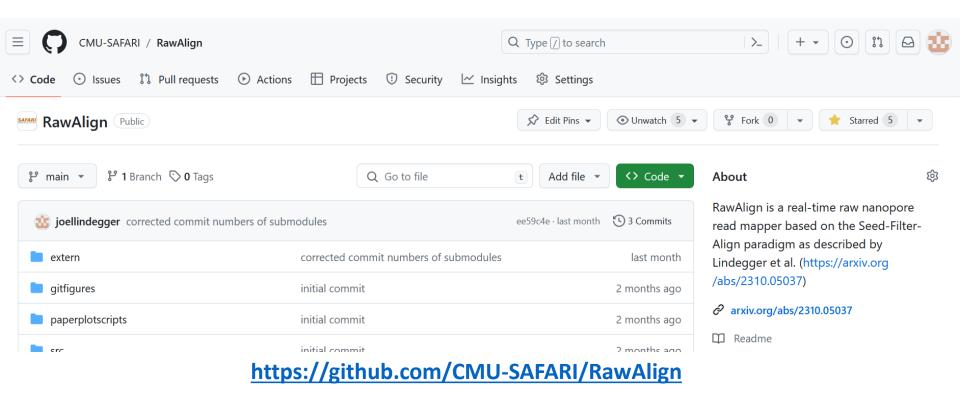
Can Firtina[§] Nika Mansouri Ghiasi[§] Onur Mutlu§

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RawAlign Source Code





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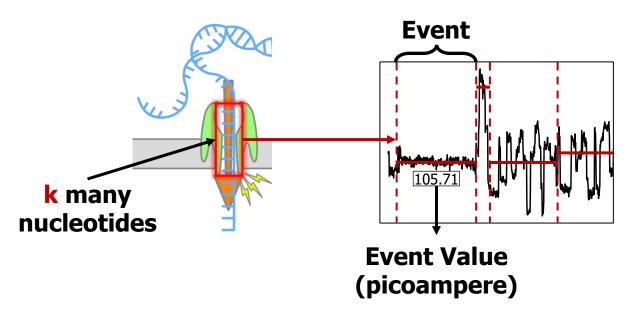


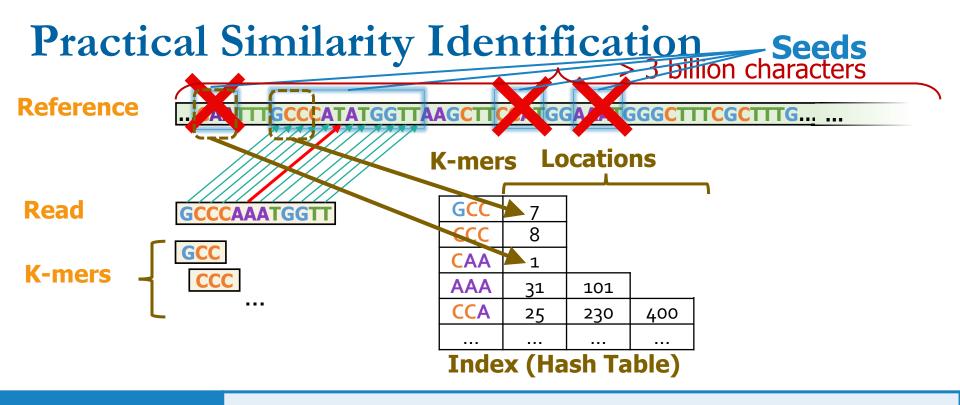
Backup Slides



Events in Raw Nanopore Signals

- Event: A segment of the raw signal
 - Corresponds to a **particular k**-mer
- Event detection finds these segments to identify k-mers
 - Start and end positions are marked by abrupt signal changes
 - Statistical methods identify these abrupt changes
 - Event value: average of signals within an event





Seeding

Determine potential matching regions (seeds) in the reference genome

Seed Filtering (e.g., Chaining)

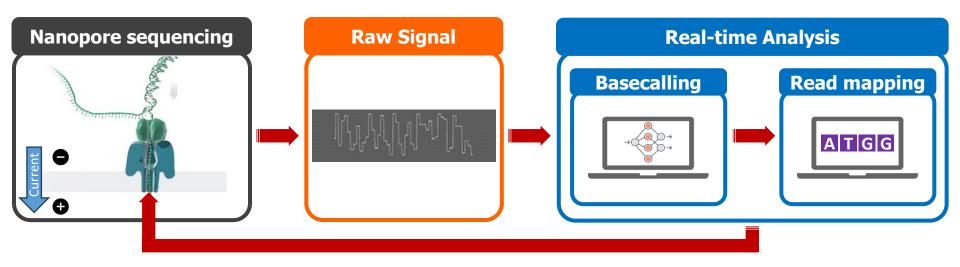
Prune some seeds in the reference genome

Alignment

Determine the exact differences between the read and the reference genome

Existing Solutions – Real-time Basecalling

Deep neural networks (**DNNs**) for translating **signals** to **bases**

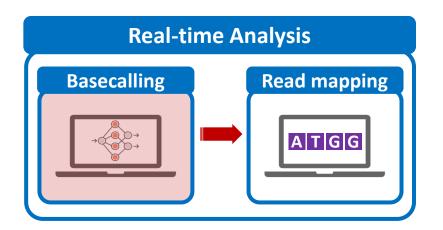


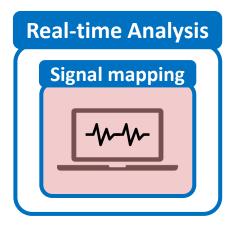
DNNs provide less noisy analysis from basecalled sequences

Costly and power-hungry computational requirements

The Problem

The existing solutions are **ineffective for large genomes**





Costly and energy-hungry computations to basecall each read:

Portable sequencing becomes challenging with resource-constrained devices

Larger number of reference regions cannot be handled accurately or quickly, rendering existing solutions ineffective for large genomes

SAFARI

Applications of Read Until

Depletion: Reads mapping to a particular reference genome is ejected

- Removing contaminated reads from a sample
- Relative abundance estimation
- Controlling low/high-abundance genomes in a sample
- Controlling the sequencing of depth of a genome

Enrichment: Reads not mapping to a particular reference genome is ejected

- Purifying the sample to ensure it contains only the selected genomes
- Removing the host genome (e.g., human) in contamination analysis

Applications of Run Until and Sequence Until

Run Until: Stopping the sequencing without informative decision from analysis

- Stopping when reads reach to a particular depth of coverage
- Stopping when the abundance of all genomes reach a particular threshold

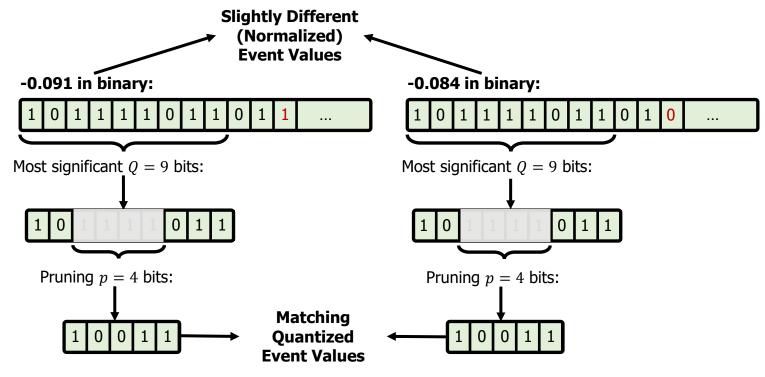
Sequence Until: Stopping the sequencing based on information decision

- Stopping when relative abundance estimations do not change substantially (for high-abundance genomes)
- Stopping when finding that the sample is contaminated with a particular set of genomes

• ...

Details: Quantizing the Event Values

- Observation: Identical k-mers generate similar raw signals
 - **Challenge:** Their corresponding event values can be slightly different
- **Key Idea:** Quantize the event values
 - To enable assigning the **same quantized value** to the **similar event values**



Average Sequenced Bases and Chunks

Tool	SARS-CoV-2	E. coli	Yeast	Green Algae	Human
	Average se	quenced ba	se length pe	r read	
UNCALLED	184.51	580.52	1,233.20	5,300.15	6,060.23
RawHash	513.95	1,376.14	2,565.09	4,760.59	4,773.58
	Average seque	enced numb	er of chunks	s per read	
Sigmap	1.01	2.11	4.14	5.76	10.40
RawHash	1.24	3.20	5.83	10.72	10.70

RawHash reduces sequencing time and cost for large genomes

up to **1.3**× compared to UNCALLED

Although Sigmap processes less number of chunks than RawHash, it fails to provide real-time analysis capabilities for large genomes

Breakdown Analysis of the RawHash Steps

	Fraction of entire runtime (%)								
Tool	SARS-CoV-2	E. coli	Yeast	Green Algae	Human				
File I/O	0.00	0.00	0.00	0.00	0.00				
Signal-to-Event	21.75	1.86	1.01	0.53	0.02				
Sketching	0.74	0.06	0.04	0.03	0.00				
Seeding	3.86	4.14	3.52	6.70	5.39				
Chaining	73.50	93.92	95.42	92.43	94.46				
Seeding + Chaining	77.36	98.06	98.94	99.14	99.86				

The entire runtime is **bottlenecked by the chaining step**

Required Computation Resources in Indexing

Tool	Contamination	SARS-CoV-2	E. coli	Yeast	Green Algae	Human	Relative Abundance
			CPU Ti	me (sec)			
UNCALLED	8.72	9.00	11.08	18.62	285.88	4,148.10	4,382.38
Sigmap	0.02	0.04	8.66	24.57	449.29	36,765.24	40,926.76
RawHash	0.18	0.13	2.62	4.48	34.18	1,184.42	788.88
			Real tin	me (sec)			
UNCALLED	1.01	1.04	2.67	7.79	280.27	4,190.00	4,471.82
Sigmap	0.13	0.25	9.31	25.86	458.46	37,136.61	41,340.16
RawHash	0.14	0.10	1.70	2.06	15.82	278.69	154.68
			Peak men	nory (GE	3)		
UNCALLED	0.07	0.07	0.13	0.31	11.96	48.44	47.81
Sigmap	0.01	0.01	0.40	1.04	8.63	227.77	238.32
RawHash	0.01	0.01	0.35	0.76	5.33	83.09	152.80

The indexing step of RawHash is **orders of magnitude faster** than the indexing steps of UNCALLED and Sigmap, especially **for large genomes**

RawHash requires larger memory space than UNCALLED

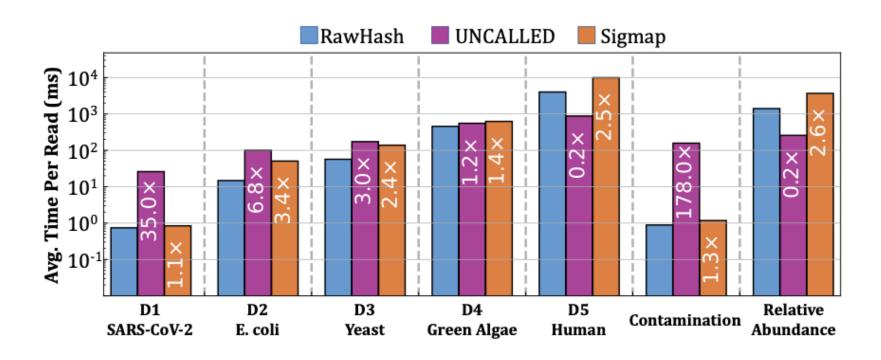
Required Computation Resources in Mapping

Tool	Contamination	SARS-CoV-2	E. coli	Yeast	Green Algae	Human	Relative Abundance
			CPU '	Time (sec)			
UNCALLED	265,902.26	36,667.26	35,821.14	8,933.52	16,769.09	262,597.83	586,561.54
Sigmap	4,573.18	1,997.84	23,894.70	11,168.96	31,544.55	4,837,058.90	11,027,652.91
RawHash	3,721.62	1,832.56	8,212.17	4,906.70	25,215.23	2,022,521.48	4,738,961.77
			Real	time (sec)			
UNCALLED	20,628.57	2,794.76	1,544.68	285.42	2,138.91	8,794.30	19,409.71
Sigmap	6,725.26	3,222.32	2,067.02	1,167.08	2,398.83	158,904.69	361,443.88
RawHash	3,917.49	1,949.53	957.13	215.68	1,804.96	65,411.43	152,280.26
			Peak m	emory (GB)			
UNCALLED	0.65	0.19	0.52	0.37	0.81	9.46	9.10
Sigmap	111.69	28.26	111.11	14.65	29.18	311.89	489.89
RawHash	4.13	4.20	4.16	4.37	11.75	52.21	55.31

The mapping step of RawHash is **significantly faster than Sigmap** for all genomes, and **faster than UNCALLED for small genomes**

RawHash requires larger memory space than UNCALLED

Average Mapping Time per Read



The mapping step of RawHash is **significantly faster than Sigmap** for all genomes, and **faster than UNCALLED for small genomes**

Parameter Configurations

Tool	Contamination	SARS-CoV-2	E. coli	Yeast	Green Algae	Human	Relative Abundance
RawHash	-x viral -t 32	-x viral -t 32	-x sensitive -t 32	-x sensitive -t 32	-x fast -t 32	-x fast -t 32	-x fast -t 32
UNCALLED	map -t 32						
Sigmap	-m -t 32						
Minimap2	-x map-ont -t 32						

Preset (-x) Corresponding parameters		Usage		
viral	-e 5 -q 9 -1 3	Viral genomes		
sensitive	-e 6 -q 9 -1 3	Small genomes (i.e., < 50M bases)		
fast	-e 7 -q 9 -1 3	Large genomes (i.e., > 50M bases)		



Versions

Tool	Version	Link to the Source Code
RawHash	0.9	https://github.com/CMU-SAFARI/RawHash/tree/8042b1728e352a28fcc79c2efd80c8b631fe7bac
UNCALLED	2.2	https://github.com/skovaka/UNCALLED/tree/74a5d4e5b5d02fb31d6e88926e8a0896dc3475cb
Sigmap	0.1	https://github.com/haowenz/sigmap/tree/c9a40483264c9514587a36555b5af48d3f054f6f
Minimap2	2.24	https://github.com/lh3/minimap2/releases/tag/v2.24



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