

Chunk Reduction for Multi-Parameter Persistent Homology

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FWF

Der Wissenschaftsfonds.

Multi-Parameter Persistent Homology

Multi-parameter persistence describes the *changes in homology* of datasets evolving along *two or more (independent) scale parameters*

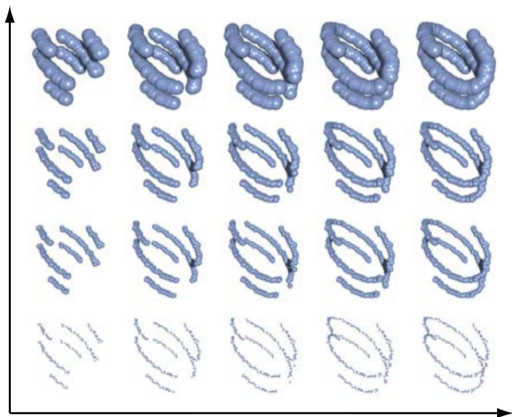


Image courtesy of [Carlsson & Zomorodian 2009]

Multi-Parameter Persistent Homology

Formally:

Given a d -filtered chain complex $C := (C_*^p)_{p \in \mathbb{R}^d}$,

the *multi-parameter persistence k^{th} module* $H_k(C)$ consists of:

- A collection of *homology spaces* $H_k(C_*^p)$ for $p \in \mathbb{R}^d$
- A collection of *linear maps* $\iota_k^{p,q} : H_k(C_*^p) \rightarrow H_k(C_*^q)$ induced by the inclusion maps at k -chain level for $p, q \in \mathbb{R}^d$ and $p \leq q$

Multi-parameter persistent homology provides a *stable and discriminative information but...*

Multi-Parameter Persistent Homology

But...

Computations scale badly with the size of the input complex

Our Goal

Design and implement a *simplification process*
drastically reducing the size of the input complex while
preserving its multi-parameter persistent homology

Outline

- *Multi-Chunk Algorithm*
- *Optimality Result*
- *Experimental Evaluation*
- *Conclusions and Future Developments*

Multi-Chunk Algorithm

Inspired by the chunk algorithm for persistent homology [Bauer et al. 2014],

We propose a *reduction algorithm* such that

given a d -filtered chain complex C returns a d -filtered chain complex \bar{C}

- *drastically smaller* than C
- *homology-equivalent* to C

C and \bar{C} are *homology-equivalent* if, for any $k \in \mathbb{N}$ and any $p, q \in \mathbb{R}^d$ with $p \leq q$,

$H_k(C_*^p)$ and $H_k(\bar{C}_*^p)$ are *isomorphic* via a map φ_k^p and each diagram

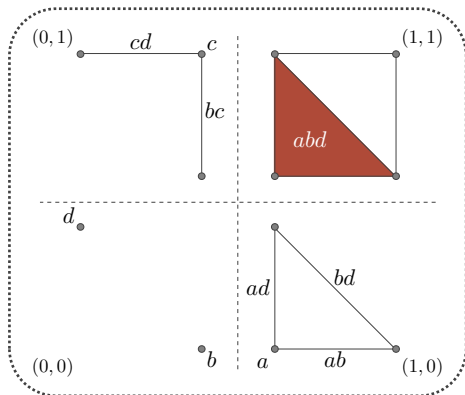
$$\begin{array}{ccc}
 H_k(C_*^p) & \longrightarrow & H_k(C_*^q) \\
 \downarrow \varphi_k^p & & \downarrow \varphi_k^q \\
 H_k(\bar{C}_*^p) & \longrightarrow & H_k(\bar{C}_*^q)
 \end{array}$$

commutes where horizontal maps are induced by inclusion maps

Multi-Chunk Algorithm

Initialization:

Given a d -filtered simplicial complex,
 each k -simplex σ can be represented by a k -column encoding:



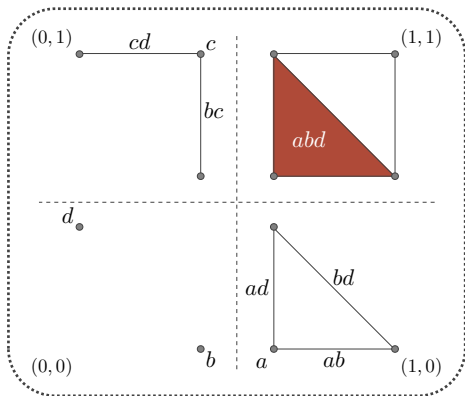
- Boundary of σ
- Dimension k
- Filtration value $v(\sigma)$
- Index $i(\sigma)$

where i is a **total order** on the simplices compatible with the filtering function v

Multi-Chunk Algorithm

Initialization:

Given a d -filtered simplicial complex,
each k -simplex σ can be represented by a k -column encoding:



- Boundary of σ { b, d }
- Dimension k 1
- Filtration value $v(\sigma)$ (1, 0)
- Index $i(\sigma)$ 9

where i is a **total order** on the simplices compatible with the filtering function v

Multi-Chunk Algorithm

		$(0,0)$			$(0,1)$			$(1,0)$			$(1,1)$
i	σ	1	2	3	4	5	6	7	8	9	10
		b	d	c	bc	cd	a	ab	ad	bd	abd
$(0,0)$	1	b			1			1		1	
	2	d				1			1	1	
	3	c			1	1					
$(0,1)$	4	bc									
	5	cd									
	6	a						1	1		
$(1,0)$	7	ab									1
	8	ad									1
	9	bd									1
$(1,1)$	10	abd									



Multi-Chunk Algorithm

Multi-chunk algorithm offers an immediate *parallelization* scheme in shared memory and it consists of *three phases*:

I - Local Reduction

II - Compression

III - Removal of Local Pairs

Local Pivot:

A column σ has a *local pivot* iff the element τ with *maximal index* in the boundary of σ is such that $v(\tau)=v(\sigma)$

Multi-Chunk Algorithm

		$(0,0)$			$(0,1)$		$(1,0)$			$(1,1)$	
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Multi-Chunk Algorithm

Phase I: Local Reduction

Proceed in *decreasing dimension* k and traverse the k -columns in *increasing order w.r.t. i*

*Goal: Label the columns as **local** or **global***

Given an *unlabeled* k -column σ , while

- σ has a local pivot and
- there is a k -column σ' with the same local pivot and $i(\sigma) < i(\sigma')$

perform the *column addition* $\sigma \leftarrow \sigma + \lambda\sigma'$ (λ is s.t. the local pivot of σ disappears)

If, at the end of the loop, the column σ *does not have a local pivot*

- σ is labeled as **global**

otherwise,

- σ is labeled as **local negative** and its local pivot as **local positive**

Multi-Chunk Algorithm

		$(0,0)$			$(0,1)$			$(1,0)$			$(1,1)$
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Multi-Chunk Algorithm

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Multi-Chunk Algorithm

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Multi-Chunk Algorithm

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Multi-Chunk Algorithm

Phase II: **Compression**

*Goal: Simplify the boundary of the **global** columns*

Given a *global* k -column σ , while

- the boundary of σ contains local positive or negative elements

pick the local $(k-1)$ -column τ in the boundary of σ with maximal index i

If τ is **local negative**,

- remove τ from the boundary of σ

If τ is **local positive**

- perform the column addition $\sigma \leftarrow \sigma + \lambda\sigma'$

where σ' is s.t. (τ, σ') is a local pair and λ is such that τ disappears



Multi-Chunk Algorithm

		(0,0)			(0,1)		(1,0)			(1,1)	
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Multi-Chunk Algorithm

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Multi-Chunk Algorithm

Phase III: Removal of Local Pairs

*Traverse the columns and **remove** all the columns labeled as **local positive** or **local negative***

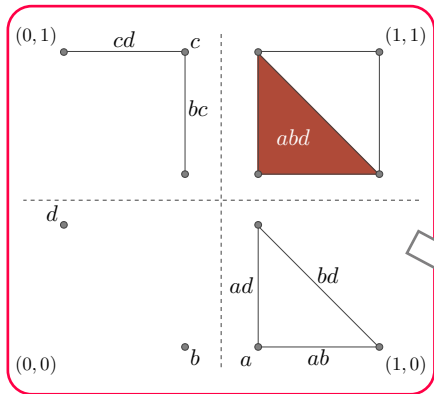
Theorem

*Remaining columns generate a d -filtered chain complex having the **same multi-parameter persistent homology** as the input (they are homotopy-equivalent)*

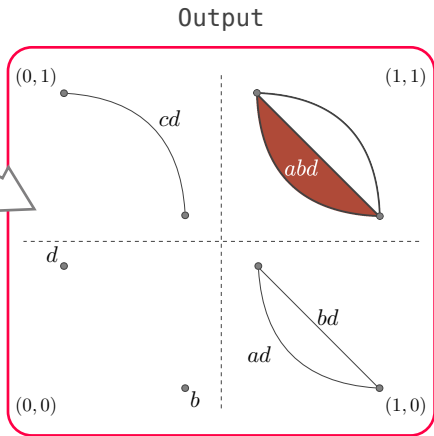
Multi-Chunk Algorithm

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Multi-Chunk Algorithm



Input



Output

Multi-Chunk Algorithm

Remarks

- In Phase I, to *proceed in decreasing dimension* avoids performing any column additions on local positive columns
- Algorithm operates *independently* on columns of the same value (called *chunks*)

Proposition

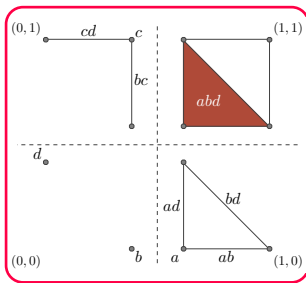
Multi-chunk algorithm has *time complexity* $O(m\ell^3 \log \ell + gn\ell \log \ell)$ and *space complexity* $O(n\ell + g^2)$ where:

- n is the size of the input complex
- m is the number of chunks
- ℓ is the maximal size of a chunk
- g is the number of global columns



Optimality Result

- $C_*^{<p} := \sum_{q < p} C_*^q$
- $\gamma_k^p(C) := \dim C_k^p - \dim C_k^{<p}$
- $\delta_k^p(C) := \dim(\ker \iota_{k-1}^p) + \dim(\text{coker } \iota_k^p)$



$$\gamma_1^{(1,0)}(C) = 3 > 2 = \delta_1^{(1,0)}(C)$$

Proposition

For any d -filtered chain complex D quasi-isomorphic to the input complex C ,

$$\gamma_k^p(D) \geq \delta_k^p(C)$$

Theorem

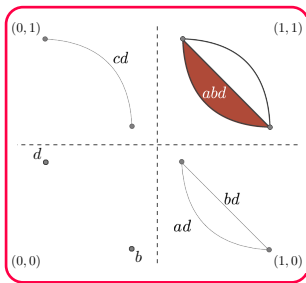
Let \bar{C} be the d -filtered chain complex complex obtained as output, then

$$\gamma_k^p(\bar{C}) = \delta_k^p(C)$$



Optimality Result

- $C_*^{<p} := \sum_{q < p} C_*^q$
- $\gamma_k^p(C) := \dim C_k^p - \dim C_k^{<p}$
- $\delta_k^p(C) := \dim(\ker \iota_{k-1}^p) + \dim(\text{coker } \iota_k^p)$



$$\gamma_1^{(1,0)}(\bar{C}) = 2 = \delta_1^{(1,0)}(C)$$

Proposition

For any d -filtered chain complex D quasi-isomorphic to the input complex C ,

$$\gamma_k^p(D) \geq \delta_k^p(C)$$

Theorem

Let \bar{C} be the d -filtered chain complex complex obtained as output, then

$$\gamma_k^p(\bar{C}) = \delta_k^p(C)$$



Experimental Evaluation

We have experimentally compared the performances of our approach with the simplification process based on *discrete Morse theory* proposed in [Scaramuccia et al. 2018]

Dataset	Size		Time (sec.)				Memory Usage (GB)	
	Input	Output	Chunk		DMT		Chunk	DMT
			Prep.	Simpl.	Prep.	Simpl.		
Eros	2.9 M	202 K	1.7	0.8	2.7	15.8	0.36	0.46
Donna	3.0 M	217 K	1.8	0.8	2.8	16.9	0.38	0.48
Chinese Dragon	3.9 M	321 K	2.5	1.1	3.9	22.3	0.52	0.64
Circular Box	4.2 M	365 K	2.9	1.2	4.3	24.0	0.68	0.68
Ramesses	5.0 M	407 K	3.4	1.3	5.5	29.4	0.68	0.81
Pensatore	6.0 M	369 K	3.8	1.6	6.8	34.3	0.76	0.97
Raptor	6.0 M	260 K	4.4	1.7	5.4	32.3	0.73	0.93
Neptune	12.0 M	893 K	8.4	4.4	14.9	69.2	1.52	1.94
Cube 1	590 K	67 K	0.5	0.3	0.7	3.2	0.09	0.10
Cube 2	2.4 M	264 K	1.8	1.1	2.6	13.1	0.35	0.40
Cube 3	9.4 M	1.0 M	7.6	4.8	11.0	53.1	1.37	1.58
Cube 4	37.7 M	4.2 M	31.9	19.4	44.9	216.0	5.50	6.32

Conclusions and Future Developments

In Summary:

We have presented a *pre-processing procedure* for improving the computation of multi-parameter persistent homology and we have provided *theoretical and experimental evidences of its effectiveness*

Future Directions:

- Develop a *parallel implementation* with shared memory of the multi-chunk algorithm
- Evaluate the impact of the chunk algorithm for the computation of the *persistence module* and of the *persistence space*
- Compare the proposed strategy with the *minimal presentation algorithm* for persistence modules from RIVET [Lesnick & Wright 2019]

A large, faded architectural drawing of a classical building with a dome and multiple arches, serving as a background for the slide.

Thank you

*Ulderico Fugacci
TU Graz, Institute of Geometry*

C and \bar{C} are *homology-equivalent* if, for any $k \in \mathbb{N}$ and any $p, q \in \mathbb{R}^d$ with $p \leq q$,

$H_k(C_*^p)$ and $H_k(\bar{C}_*^p)$ are *isomorphic* via a map φ_k^p and each diagram

$$\begin{array}{ccc} H_k(C_*^p) & \longrightarrow & H_k(C_*^q) \\ \downarrow \varphi_k^p & & \downarrow \varphi_k^q \\ H_k(\bar{C}_*^p) & \longrightarrow & H_k(\bar{C}_*^q) \end{array}$$

commutes where horizontal maps are induced by inclusion maps

C and \bar{C} are *quasi-isomorphic* if the isomorphisms of the above diagram are induced by a collection of chain maps f_*^p such that each diagram

$$\begin{array}{ccc} C_*^p & \longrightarrow & C_*^q \\ \downarrow f_k^p & & \downarrow f_k^q \\ \bar{C}_*^p & \longrightarrow & \bar{C}_*^q \end{array}$$

commutes where horizontal maps are the inclusion maps

C and \bar{C} are *homotopy-equivalent* if there exist two collections of chain maps f_*^p and g_*^p such that they are *homotopy-inverse* (i.e., $g_*^p f_*^p \simeq \text{id}_{C_*^p}$ and $f_*^p g_*^p \simeq \text{id}_{\bar{C}_*^p}$) and each diagram

$$\begin{array}{ccc}
 C_*^p & \longrightarrow & C_*^q \\
 f_k^p \downarrow & & \downarrow f_k^q \\
 \bar{C}_*^p & \longrightarrow & \bar{C}_*^q \\
 g_k^p \uparrow & & \uparrow g_k^q
 \end{array}$$

commutes where horizontal maps are the inclusion maps

Homotopy-equivalent



Quasi-isomorphic



Homology-equivalent

Filtered chain complexes which are
homology-equivalent but not *quasi-isomorphic*

