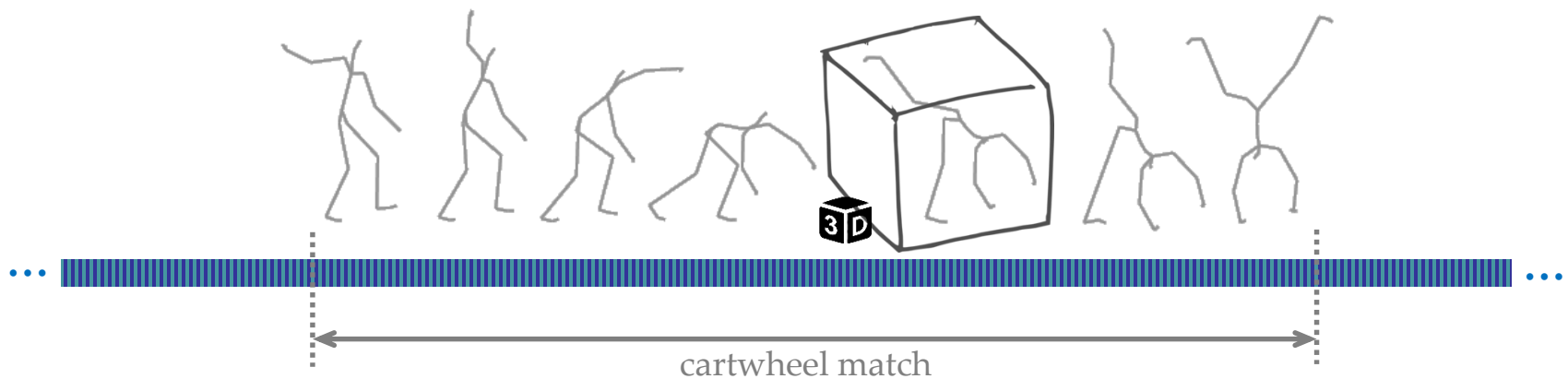


Similarity Searching in Long Sequences of Motion Capture Data

Jan Sedmidubsky, Petr Elias, Pavel Zezula



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Systems and Applications
disa.fi.muni.cz



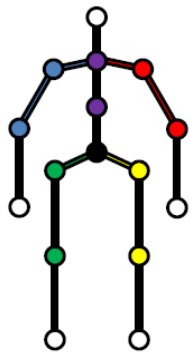
Faculty of Informatics, Masaryk
University, Czech Republic
fi.muni.cz



Introduction to Motion Capture Data

Motion Capture (mocap) Data

- Acquired by marker-based/less capturing technologies
- Complex multi-dimensional spatio-temporal data
- 3D space, 25+ body joints, 30+ frames per second
- Input for our research



*Simplified human skeleton
with 16 joints*

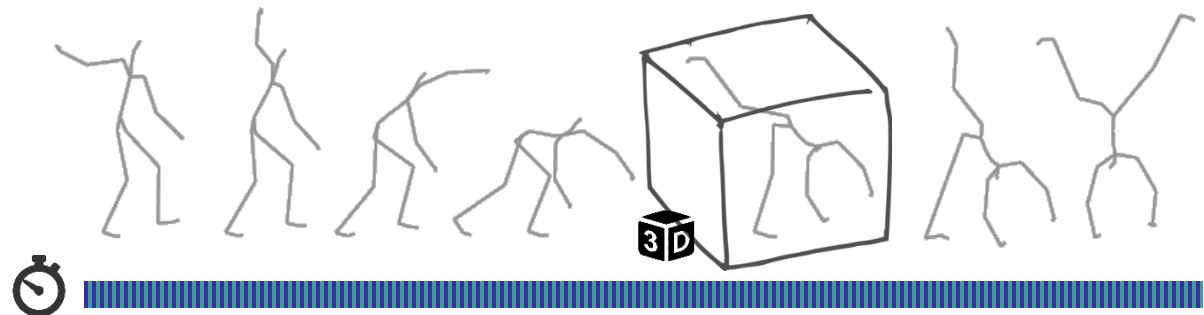


Illustration of short cartwheel motion sequence
5 seconds of 120 Hz mocap data represent 55,800 float numbers

Applications of Mocap Data



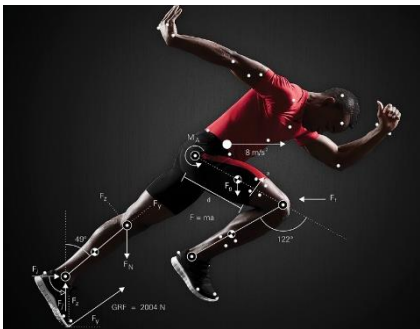
Computer Animation

Finding desired actions for a game or movie from a databank of motion recordings



Medicine

Recognizing developmental disabilities and movement disorders such as cerebral palsy

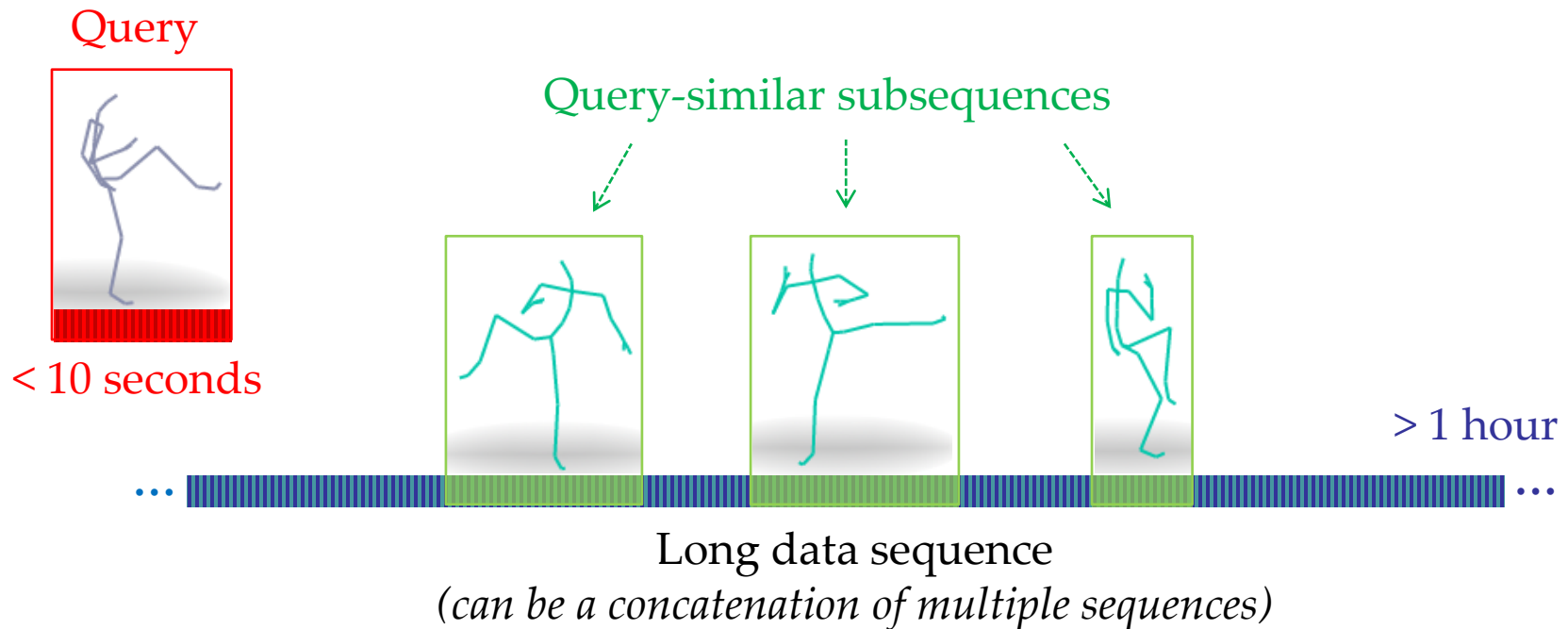


Sports

Searching for similar movement patterns to analyze athlete performance

Objective – Subsequence Matching

Objective – to develop an efficient mechanism for searching a **long data sequence** and localizing its parts that are similar to a **short query sequence**



Subsequence Matching – Challenges

- Actors have **different bodies** (*e.g., child and adult*)
- Seemingly **same actions** can be performed in **different speeds** (*faster, slower*) and **styles** (*e.g., frontal kick vs. side kick*)
- Captured data can be **noisy or incomplete**

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→ **#1 Robust Similarity Measure**

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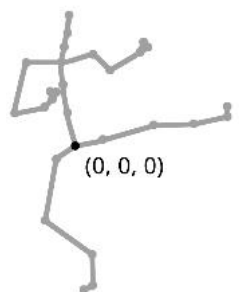
#2 Efficient Subsequence Matching

#1 Similarity Measure

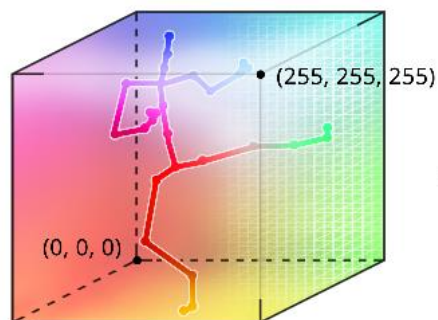
Our motion similarity – **4,096D** features + L_2 metric

- Mocap data are encoded into RGB images [Elias et al., SISAP 2015]
- Features extracted from RGB images using a deep convolutional neural network that performs very well on image data

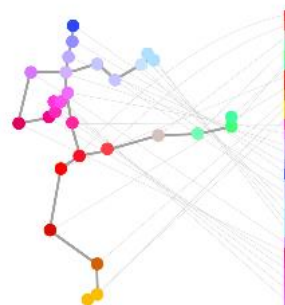
(a) Motion normalization



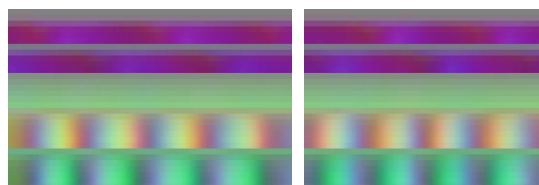
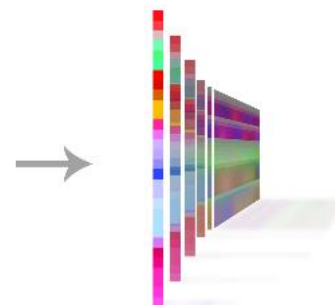
(b) Quantization of coordinates



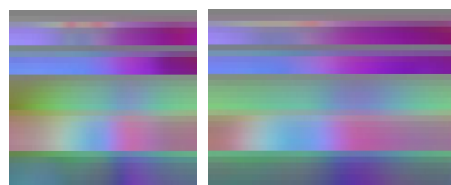
(c) Single pose visualization



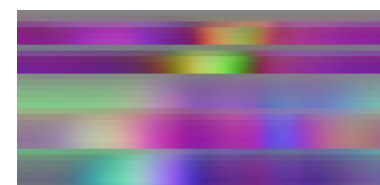
(d) Motion visualization



Rotate arms



Stand up



Cartwheel

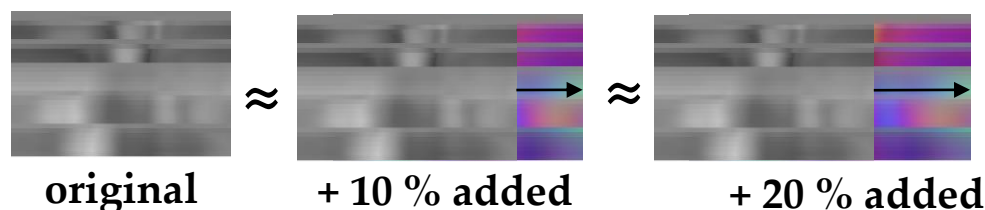
#1 Similarity Measure – Properties

- **Efficiency**

- Motions of **different lengths** have the **fixed-size** features
- L_2 comparison enables a utilization of any **metric-based index**

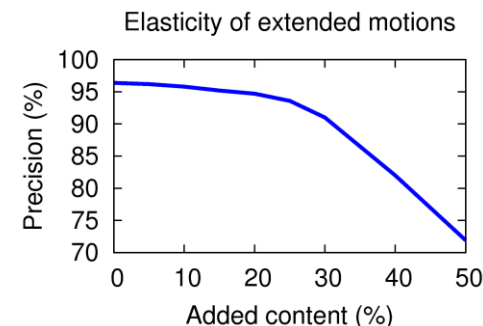
- **Effectiveness**

- Copes well with different speeds and styles of actions
- **Elasticity** – similarity distances change only slightly when **content is removed or added (important for sequence segmentation)**



Sensitivity to an added/removed content

Adding a bounded amount of extra content has a minor effect to the search precision. A similar trend can be observed when a similar amount of content is removed.



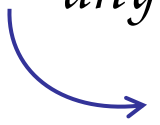
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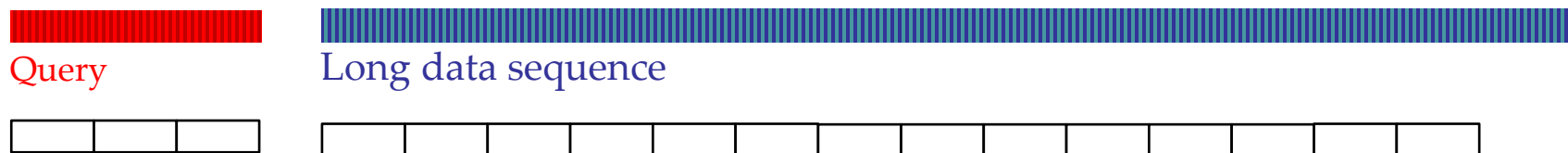


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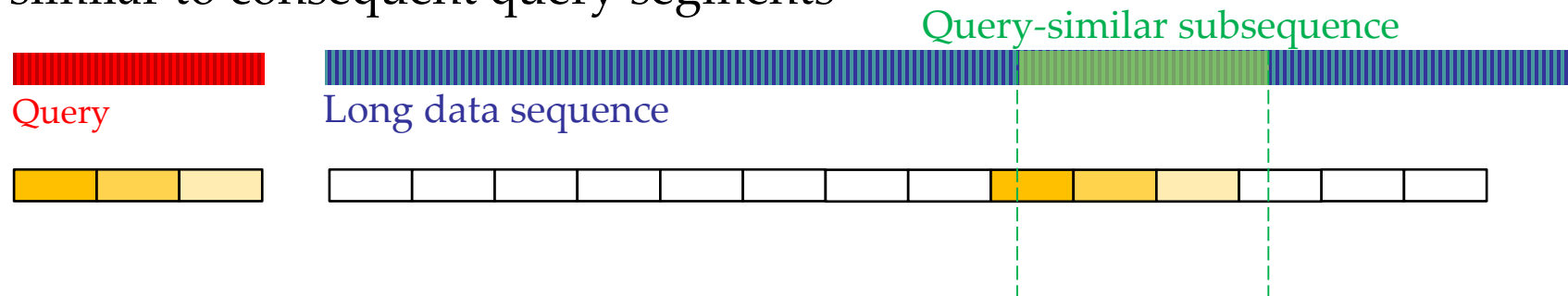
#2 Subsequence Matching

Subsequence matching:

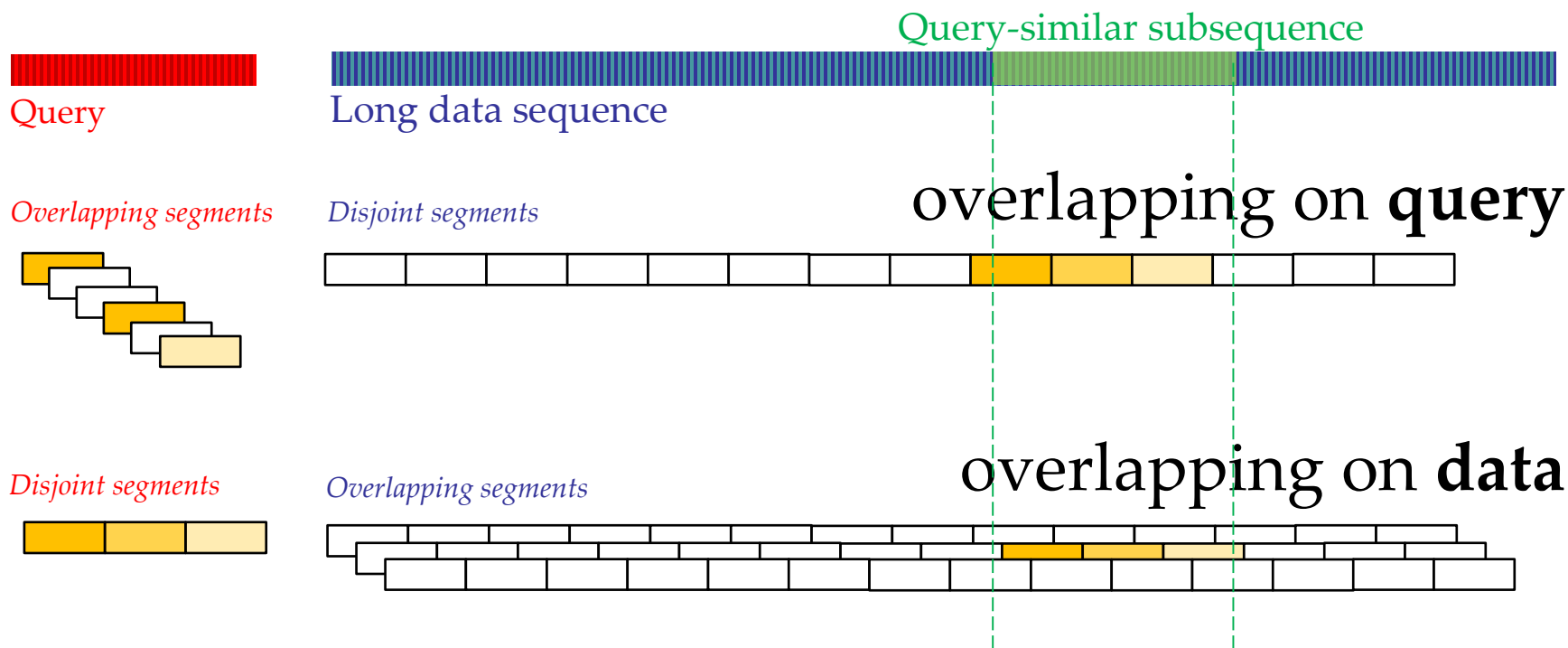
- **Segmentation** – short query and long data sequence are partitioned into parts (segments) to be meaningfully comparable (to have similar lengths)



- **Retrieval algorithm** – searching for consequent data segments that are similar to consequent query segments



#2 Segmentation – Overlapping on Query/Data

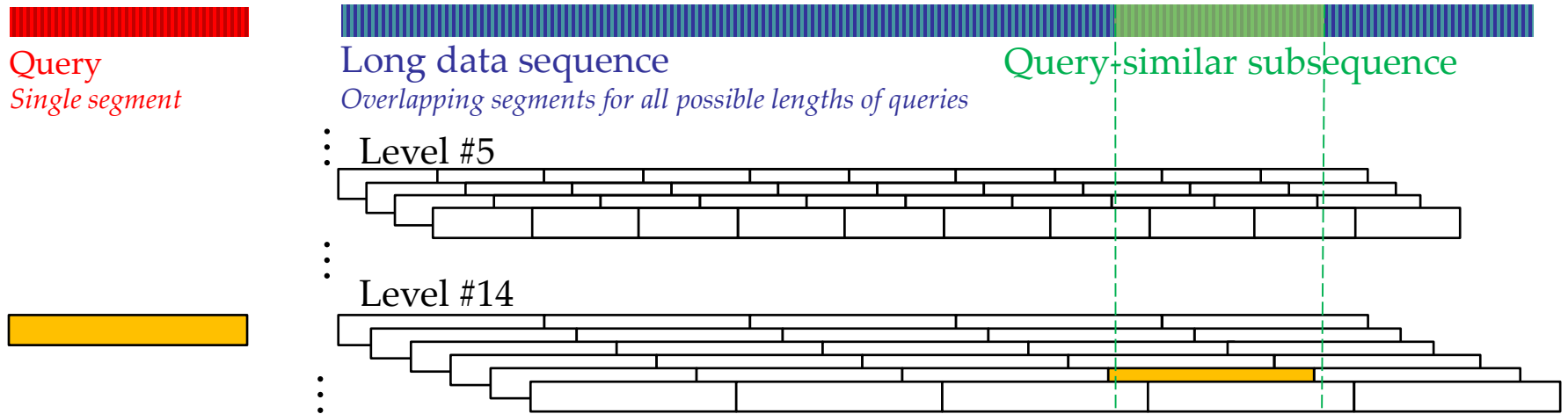


- ☹ A lot of query segments – longer queries are more expensive to evaluate
- ☹ Grouping relevant segments w.r.t. temporal information

#2 Segmentation – Naive

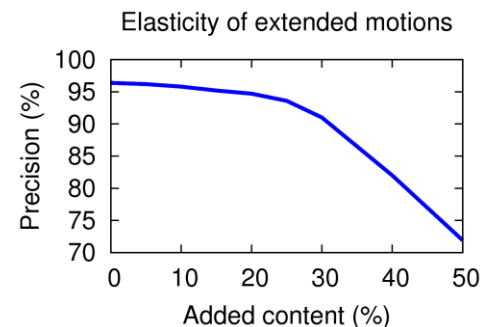
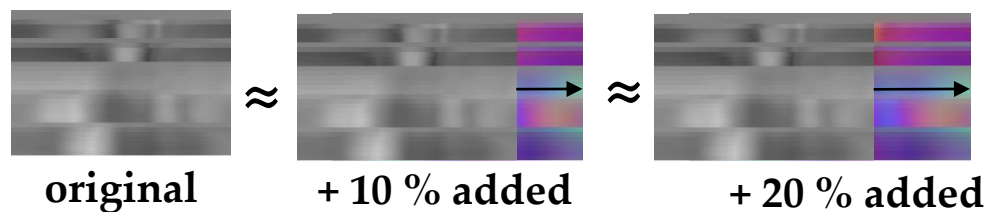
Query as a single segment – naive solution

- Query always considered as a **single segment**
- Data sequence as **multi-level overlapping segments**



- 😊 Much easier retrieval – one query, no complex post-processing
- 😞 Segment level for each query length – a huge number of data segments

#1 Similarity Measure – Elasticity Property

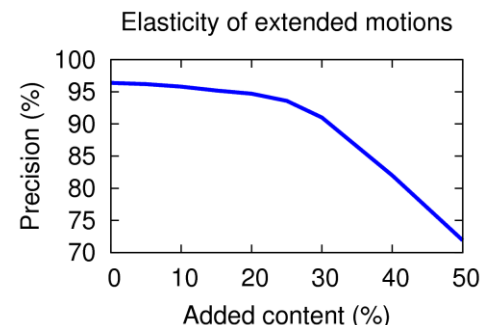
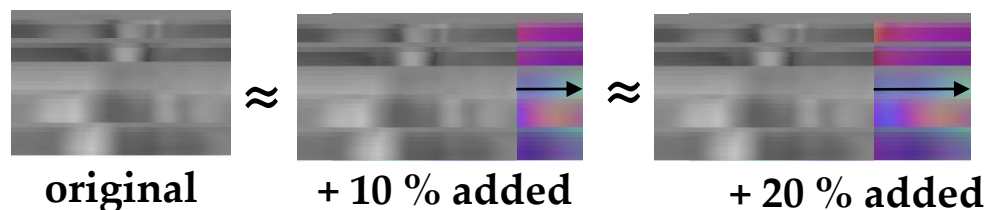


Sensitivity to an added/removed content

Adding a bounded amount of extra content has a minor effect to the search precision.

A similar trend can be observed when a similar amount of content is removed.

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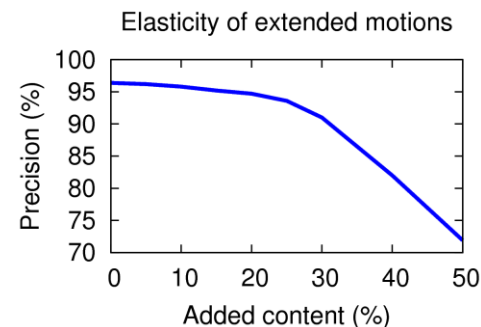
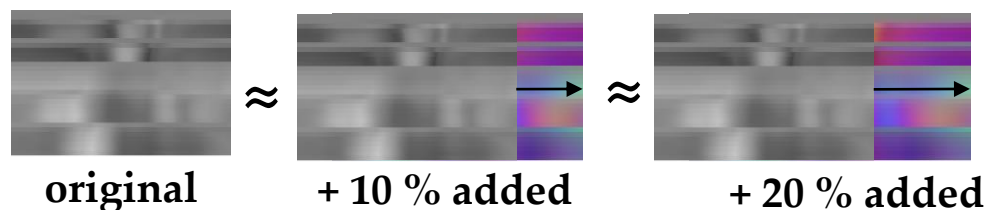
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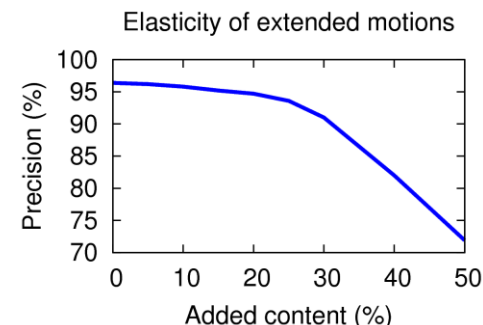
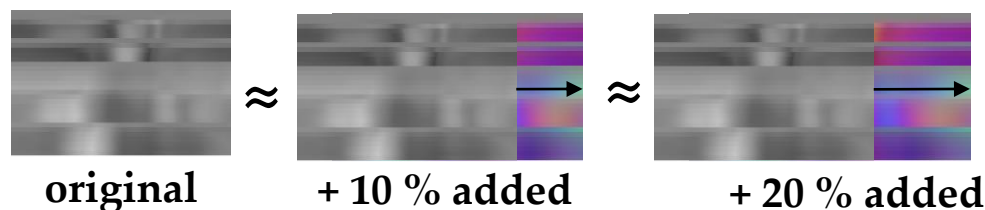
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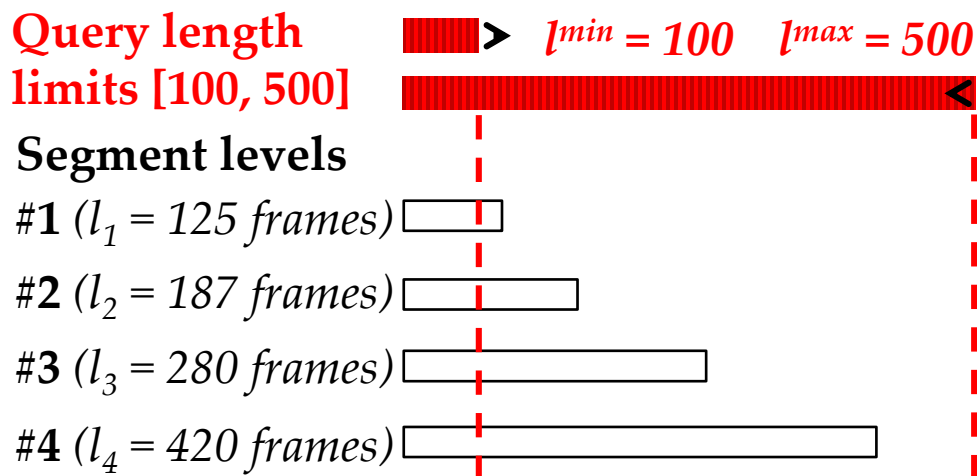
☺ The huge number of segments can be dramatically reduced!

#2 Subsequence Matching – Advanced App.

Advanced multi-level segmentation approach

- Segment lengths and number of levels depend on
 - Query length limits (l_{min} , l_{max})
 - Elasticity of the similarity measure (quantified by cf parameter)

Segmentation example for elasticity $cf = 20\%$:

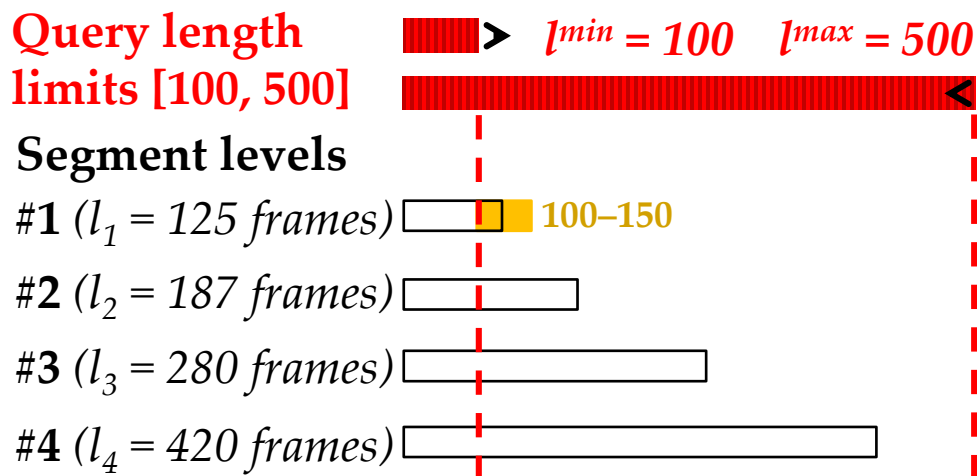


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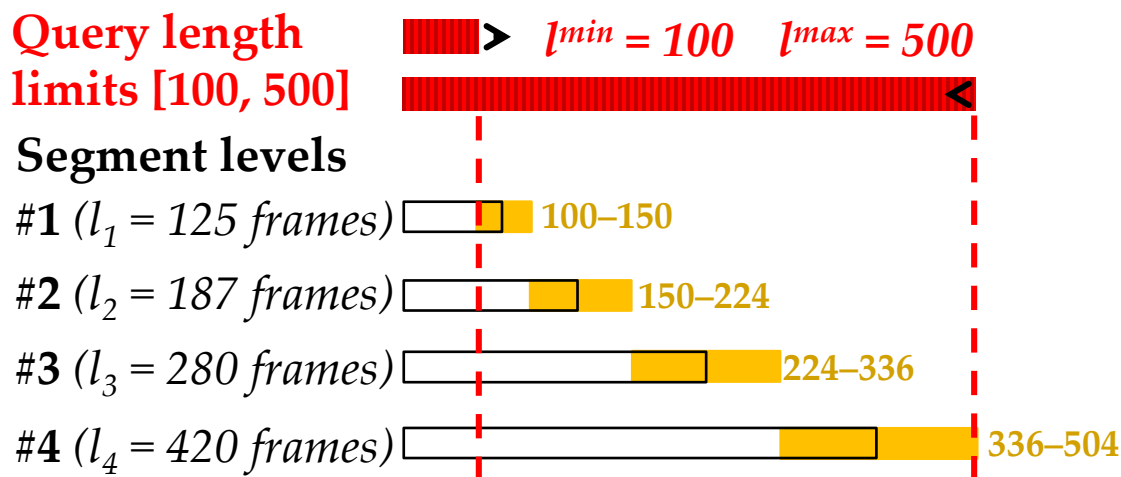


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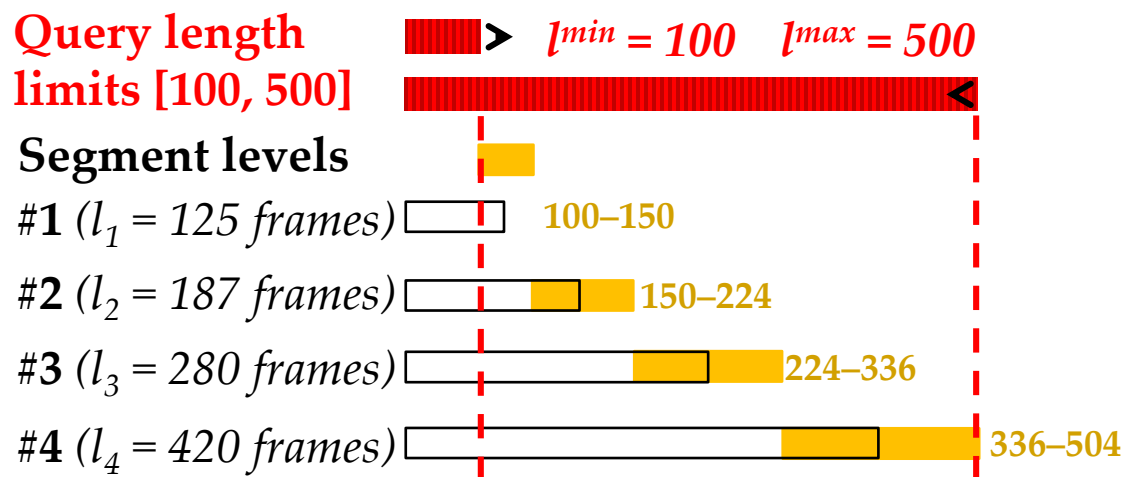


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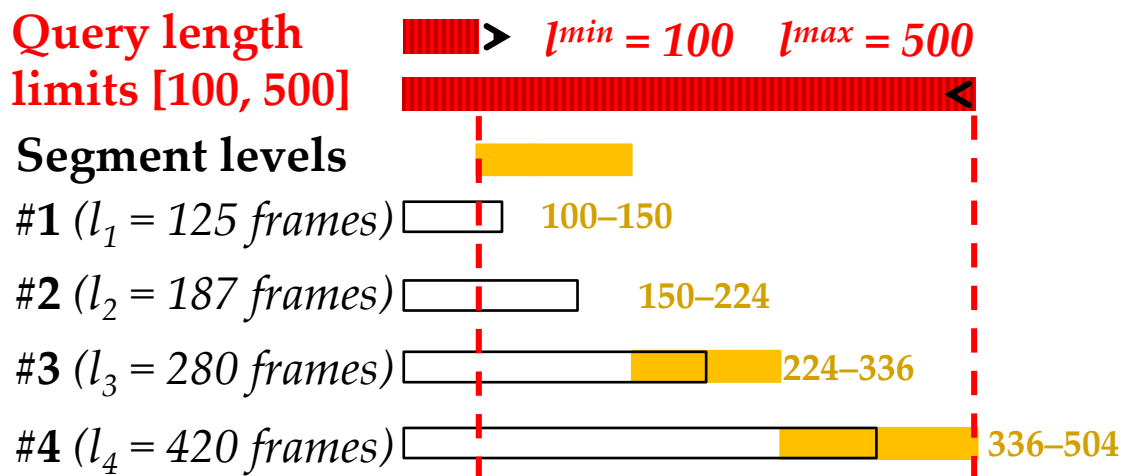


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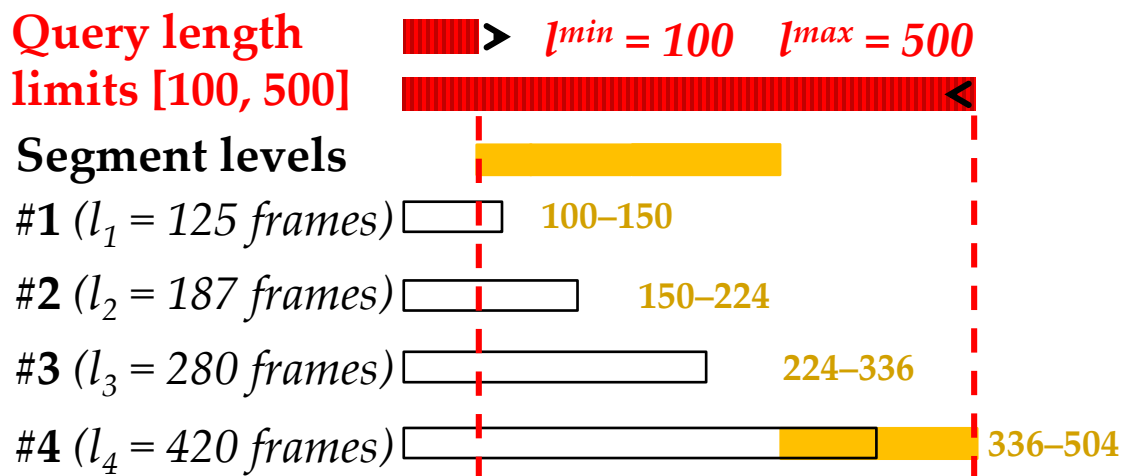


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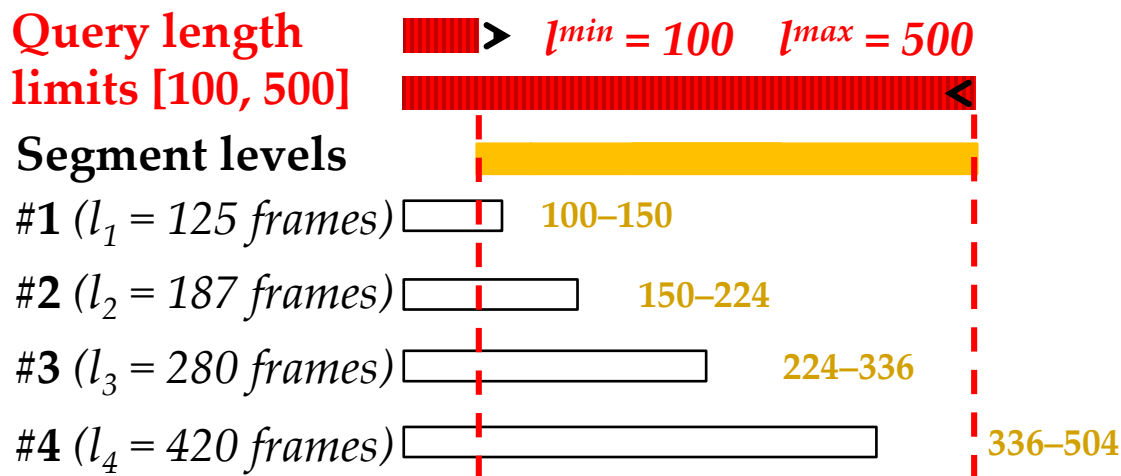


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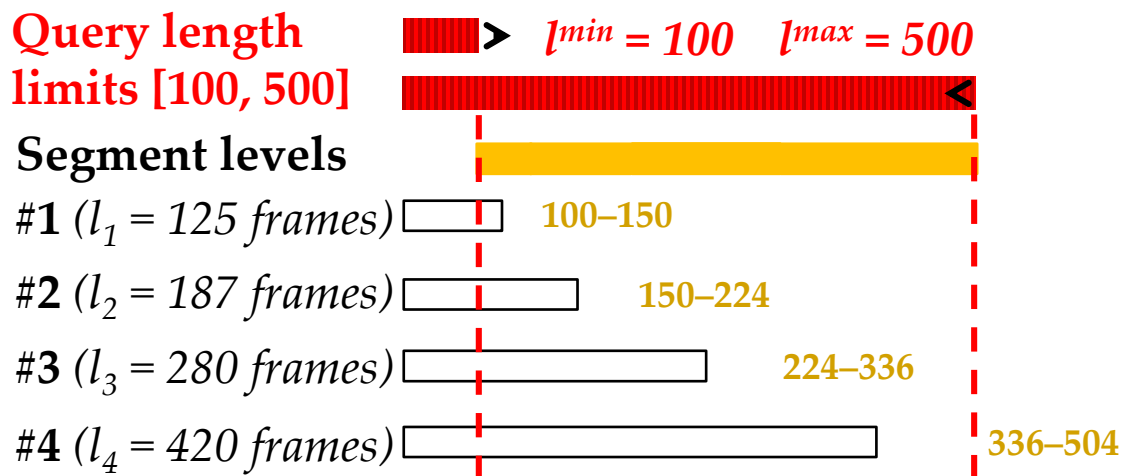


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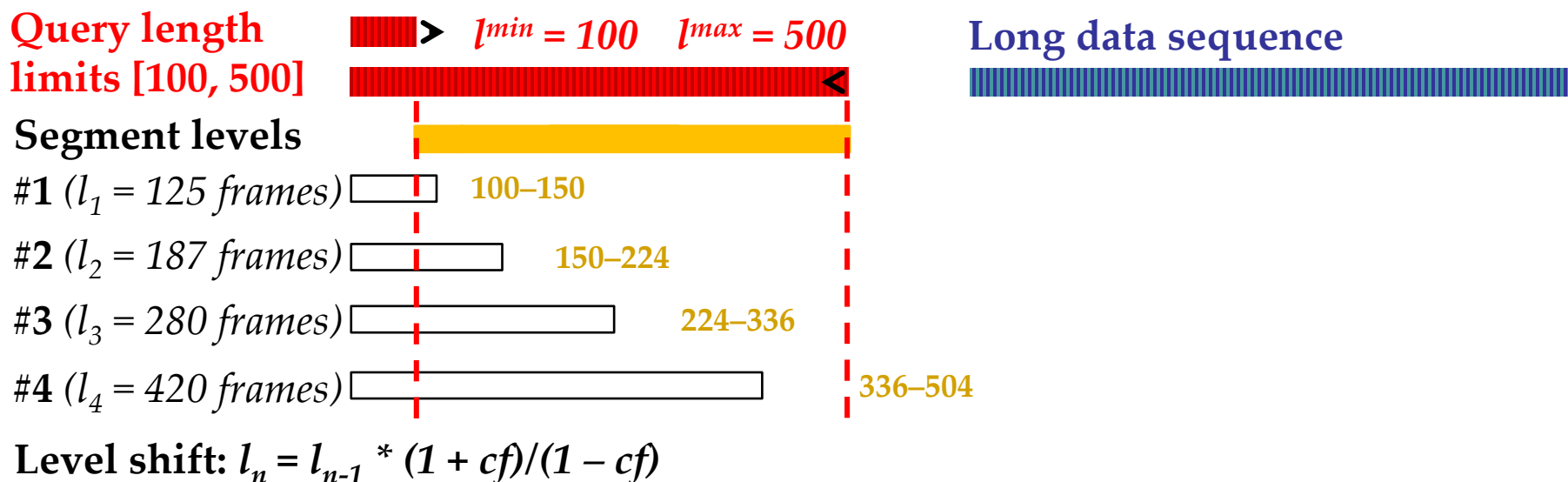
Level shift: $l_n = l_{n-1} * (1 + cf)/(1 - cf)$

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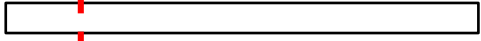
Query length limits $[100, 500]$  $l^{min} = 100$ $l^{max} = 500$

Segment levels 

#1 ($l_1 = 125$ frames)  100–150

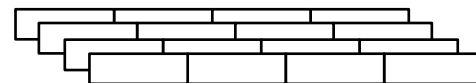
#2 ($l_2 = 187$ frames)  150–224

#3 ($l_3 = 280$ frames)  224–336

#4 ($l_4 = 420$ frames)  336–504

Level shift: $l_n = l_{n-1} * (1 + cf)/(1 - cf)$

Long data sequence 

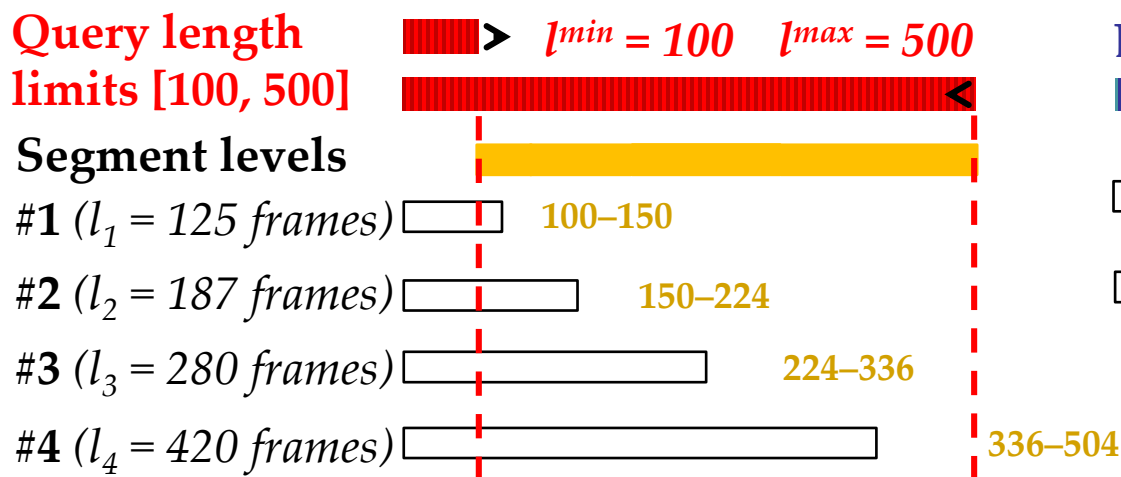


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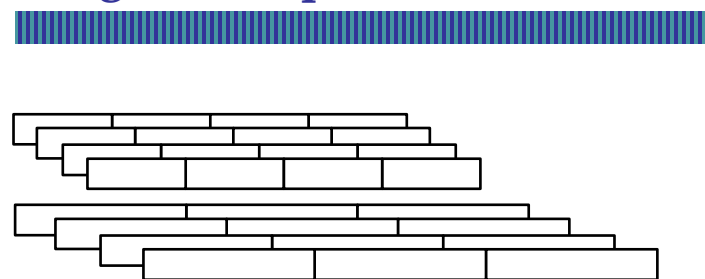
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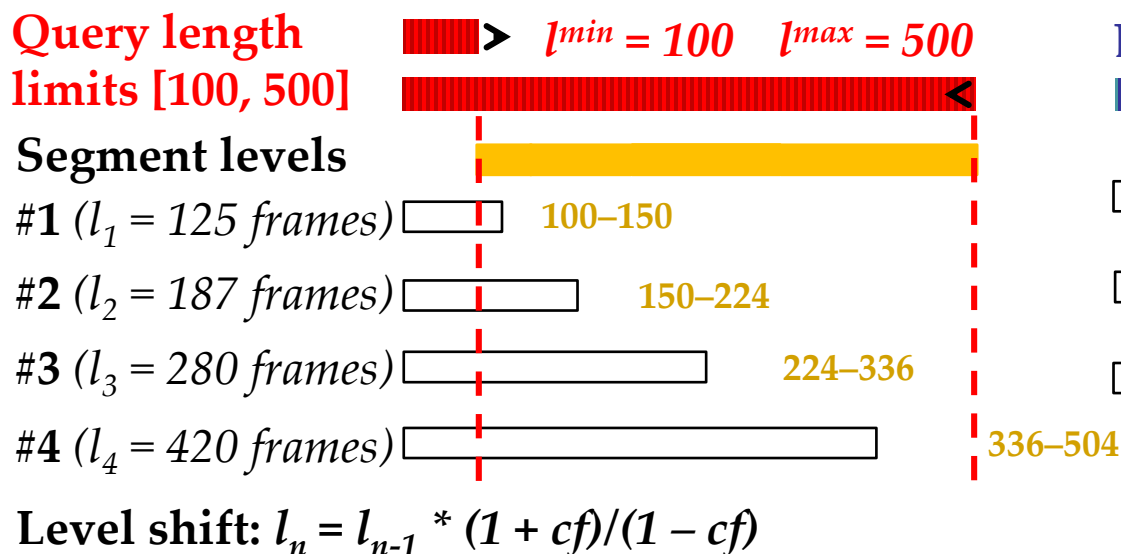


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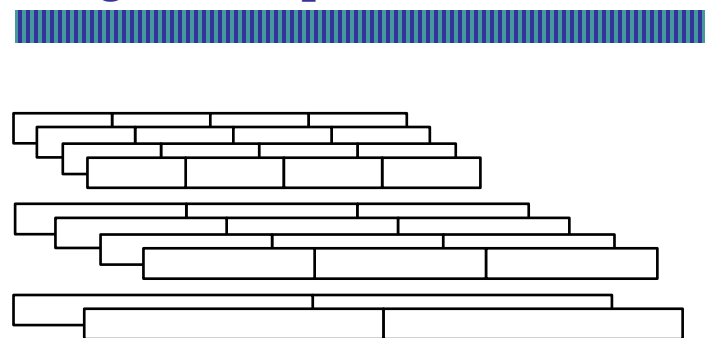
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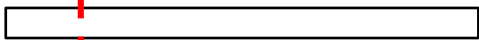
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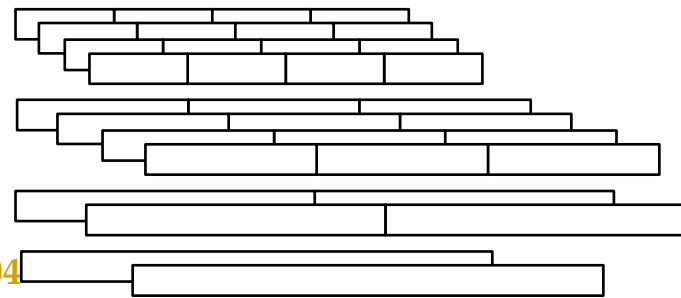
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Long data sequence 



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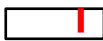
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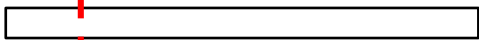
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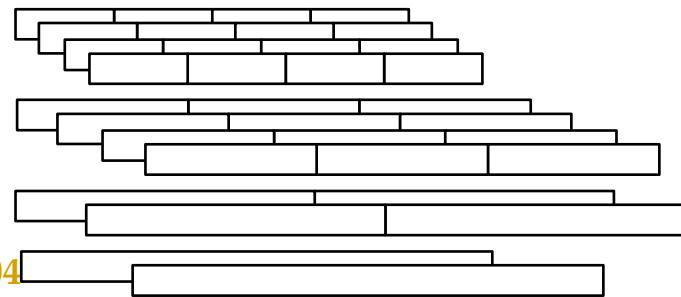
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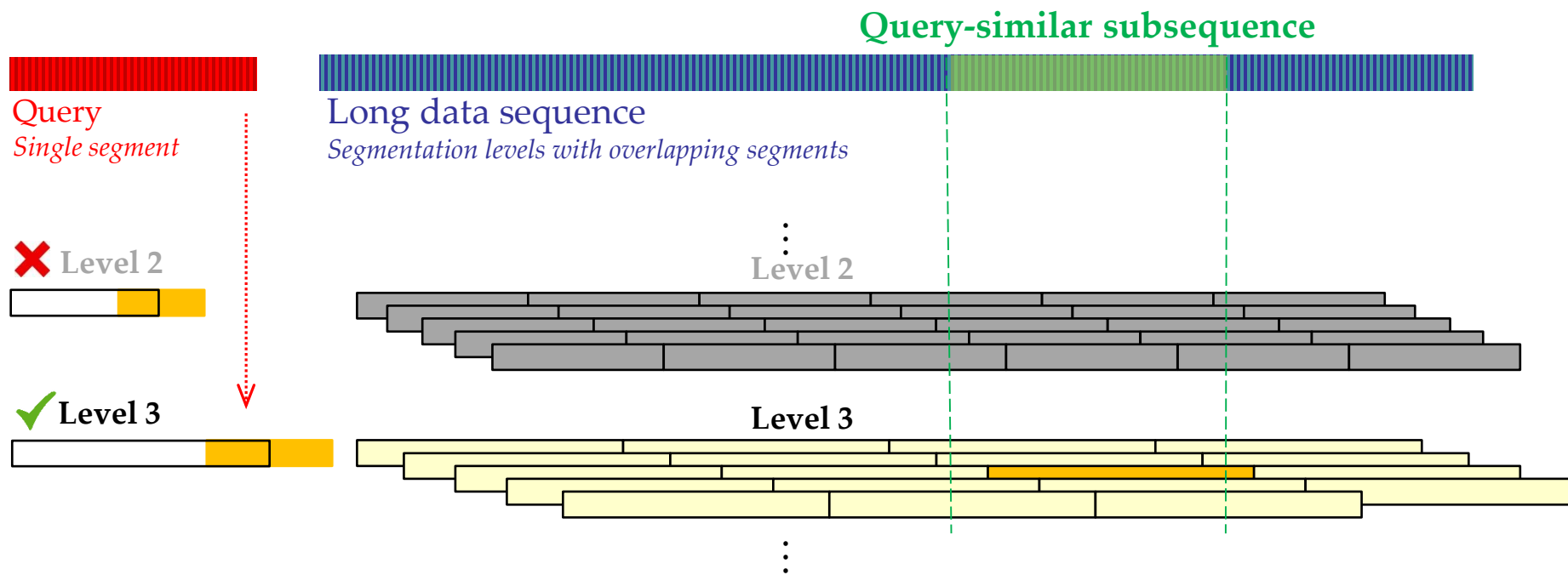
Long data sequence 



Segment shift: $l_n * cf$

#2 Subsequence Matching – Advanced App.

- Only a single query-relevant level considered for search
 - For arbitrary data subsequence of $l_{min} < \text{length} < l_{max}$, there exists a single segment that overlaps from at most $100 - cf$ [%]
- The k most similar segments presented as the query result



Segmentation in Numbers

Example:

- Data sequence of length 400,000 frames (120 Hz ~ 1 hour)
- Query length limits: $l^{min} = 100$ and $l^{max} = 500$ frames
- Example query length: 300 frames (120 Hz ~ 3 seconds)

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	Total # of data segments	Data replication	Max # of comparisons
Baseline – overlap on query	4,000	1	800,000
Baseline – overlap on data	400,000	100	1,200,000
SISAP '16 – naive	160,000,000	120,000	400,000
SISAP '16 – advanced	7,720	20	1,430

Experimental Evaluation – Advanced Approach

- **HDM05 Dataset:** 68-minute long data sequence
 - 120 Hz sampling, 31 body joints
 - Ground truth: 1,464 short subsequences in 15 categories (~queries)
- Subsequence retrieval using k -NN queries:
 - $l^{min} = 41$ frames (340ms), $l^{max} = 2,063$ frames (17.2s)
 - Different settings of elasticity $cf = \{10\%, 20\%, 30\%, 40\%, 50\%\}$

cf [%]	# of levels	# of levels		Feature extract. time [min]	Sequential scan [ms]	Precision	
		total	1st level			$k = 1$	$k = 5$
10	18	631,746	111,774	263.2	447	87.30	84.37
20	9	150,971	51,230	62.9	205	86.75	84.13
30	6	66,972	31,526	27.9	126	86.89	82.98
40	5	37,345	21,955	15.6	88	85.79	82.65
50	4	23,669	16,393	9.9	66	84.43	81.99

Conclusions

Advanced subsequence matching in mocap data

- Query always considered as a single segment
- The elasticity property of the similarity measure enables to dramatically reduce the number of data segments

Efficiency

- Searching the 68-minute sequence sequentially takes 205ms
- By applying the PPP-Codes [Novak et al., TLDKS 2016] to index data segments at each level, search times can be further decreased by **two orders of magnitude**
 - Approximate search within a **121-day long** data sequence in **1 second**

Online demo: <http://disa.fi.muni.cz/mocap-demo/>