



Temporal Action Co-Segmentation in 3D Motion Capture Data and Videos

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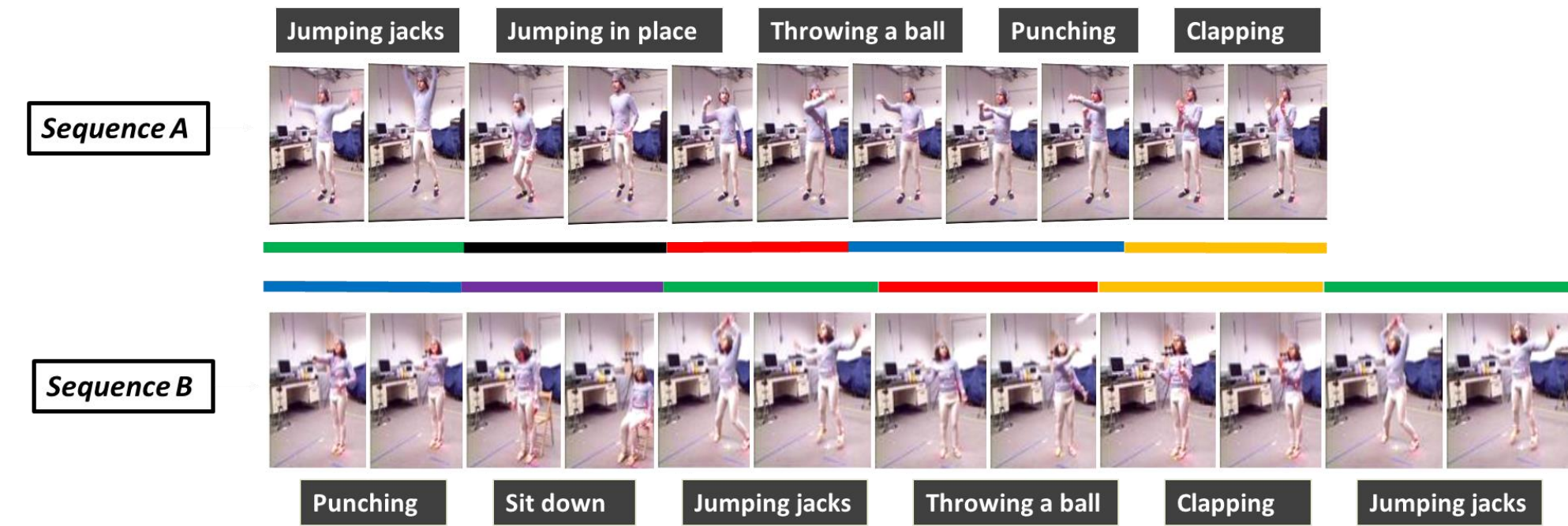
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PROBLEM

➤ Given two action sequences (of motion capture or video data), we are interested in spotting & co-segmenting all pairs of sub-sequences (commonalities [1]) that represent the same action.



- ✓ No a-priori model or labels of the actions are available.
- ✓ The number of common subsequences may be unknown.
- ✓ The sub-sequences can be located anywhere in the long sequences, may differ in duration and the corresponding actions may be performed by a different person, in different style.

MOTIVATION

The discovery of common action patterns in two or more sequences provides an efficient bottom-up way to:

- ✓ **segment** action sequences,
- ✓ **identify a set of elementary actions,**
- ✓ **build models** of the performed activities in an **unsupervised manner.**

MAIN IDEA

We propose a totally unsupervised solution to the problem of temporal action co-segmentation using **stochastic optimization by employing Particle Swarm Optimization (PSO).**

The objective function that is minimized by PSO capitalizes on **Dynamic Time Warping (DTW)** to compare two action sequences.

REFERENCES

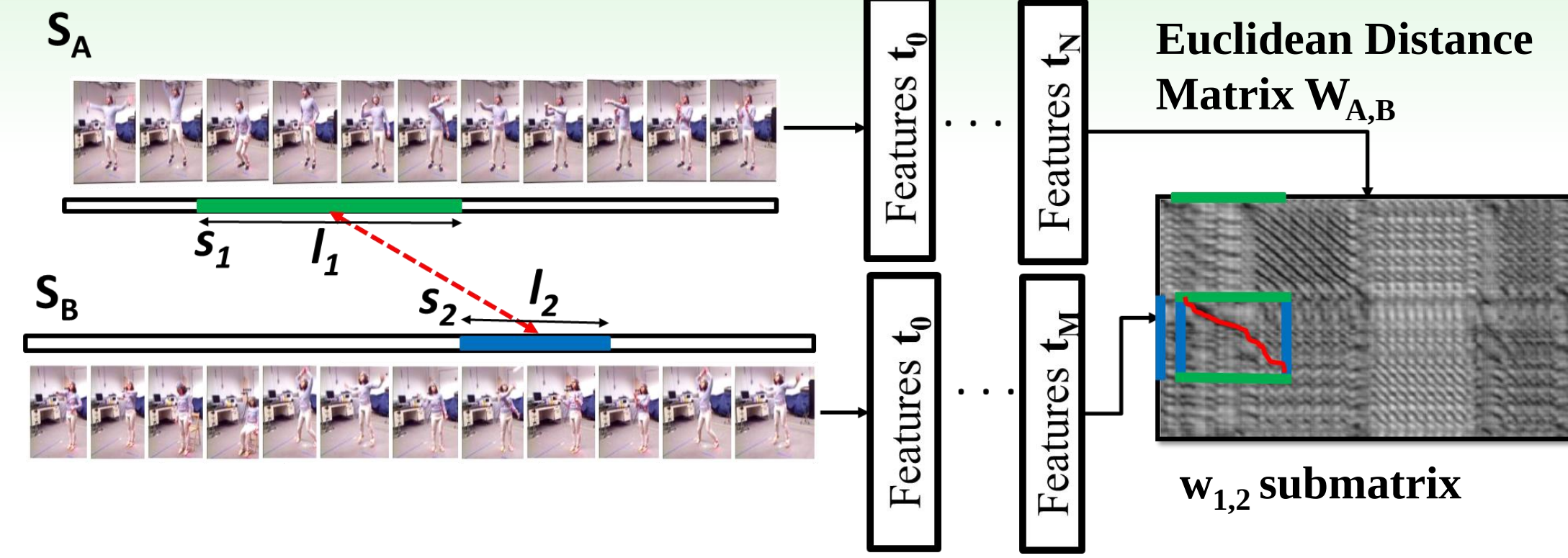
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PROPOSED FRAMEWORK

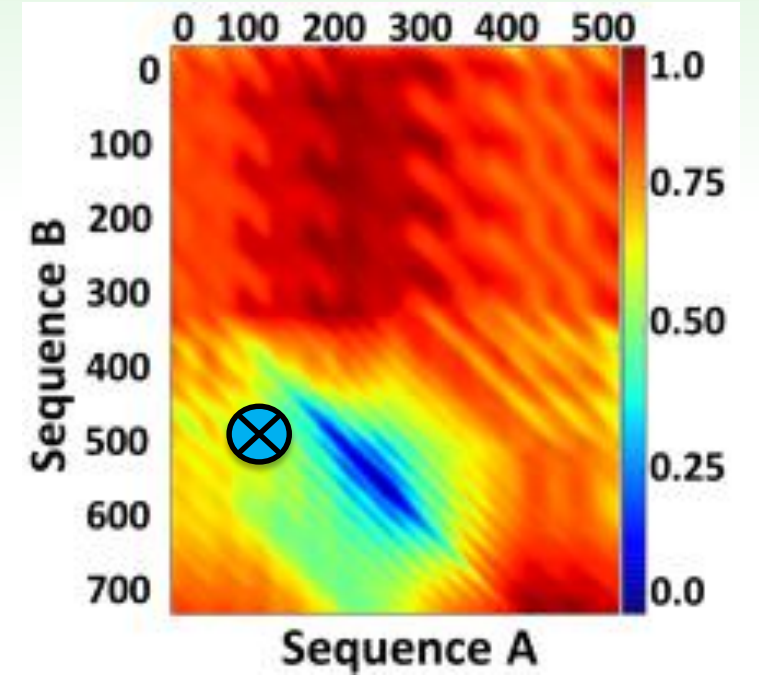
Evaluating a candidate commonality using DTW

We treat the action sequences as multivariate time-series of either:

- ✓ **3D motion capture data:** angle-based feature representation of skeletal joints.
- ✓ **or 2D video data:** motion-based features (dense trajectories [4]) in RGB videos.



- ✓ Quadruple $p = (s_p, l_p, s_{\gg}, l_{\gg})$ defines a 2D rectangle $w_{1,2}$ in $W_{A,B}$ that is a **possible commonality p**.
- ✓ Compute the alignment DTW score $D(p)$ in the $w_{1,2}$ submatrix.
- ✓ Define a **particle p** $\otimes$ in the 4D PSO search space.



Spotting a single commonality using PSO

- ✓ Define an objective function based on the $D(p)$ score and the #diagonal steps $n_p(p)$ in the optimal path p of DTW.
- ✓ Optimize (minimize) over all possible commonalities in the 4D search space using the PSO for P particles over G generations.

$$O(p) = \frac{D(p) + c}{n_p(p) + 1}$$

$$\Omega(p_i, p_j) = \frac{|R(p_i) \cap R(p_j)|}{|R(p_i)|}$$

Spotting multiple commonalities

- ✓ Define a new objective function using the normalized overlap among retrieved commonalities.
- ✓ Iteratively run PSO to retrieve N commonalities.

$$O(p) = \frac{D(p) + c}{n_p(p) + 1} \quad p_i^* = \arg \min_p \left(O(p_i) + \lambda \sum_{j=1}^{i-1} \Omega(p_i, p_j) \right)$$

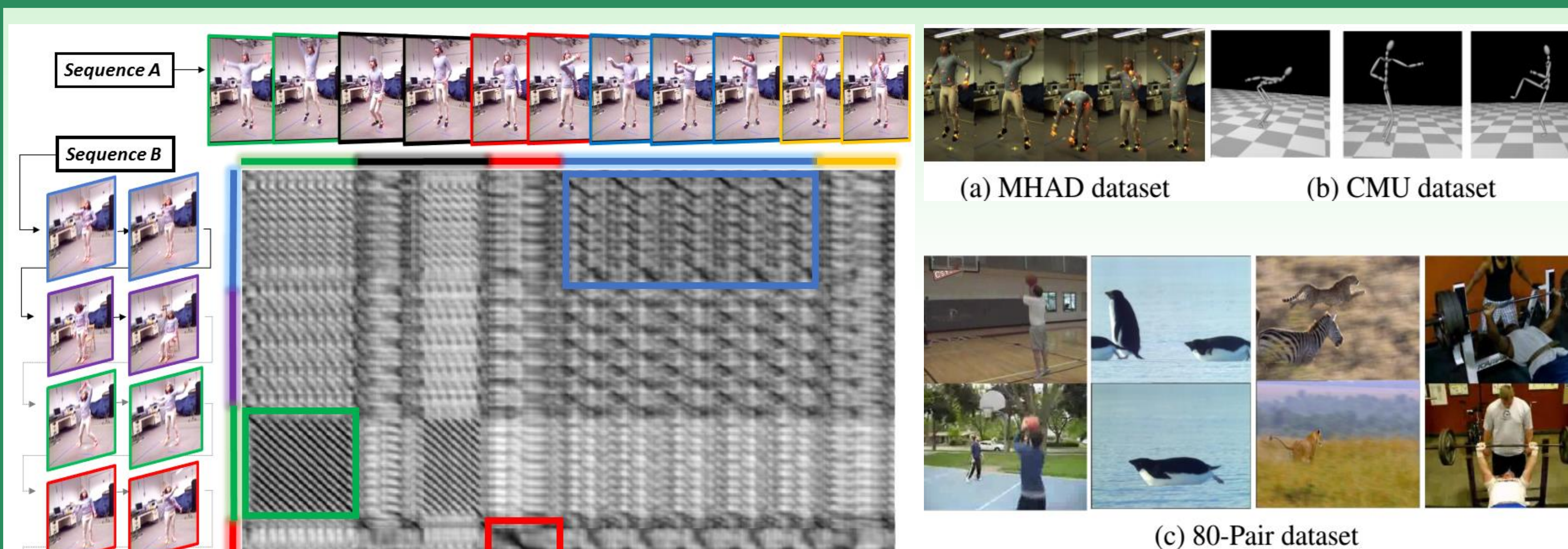
Supervised vs Unsupervised Action Co-segmentation

S-EVACO: Number of commonalities is known a-priori.

U-EVACO: The number of common actions is determined automatically by solving a model selection task.

$$j^* = \underset{j \in \{1, \dots, K-1\}}{\operatorname{argmax}} \left| \frac{1}{j} \sum_{i=1}^j O(p_i) - \frac{1}{K-j} \sum_{i=j+1}^K O(p_i) \right|$$

EXPERIMENTAL RESULTS



- **Datasets available online:** www.ics.forth.gr/cvrl/evaco
- **Contact:** papoutsas@ics.forth.gr <http://users.ics.forth.gr/~papoutsas/>
- This research received funding from the EU H2020 projects Co4Robots, ACANTO.

Datasets/Features/Info		#Pairs	#Common (per pair)	#Common (total)
MHAD101-s	3D skeletal	101	1 – 4	203
CMU86-91 [1]	3D skeletal	91	3 – 18	609
MHAD101-v	MBH, IDT HOF, HOG	101	1 – 4	203
80-pair [3]	MBH	80	1	80

Overlap scores %	3D skeletal data		Video data	
Methods / Datasets	MHAD 101-s	CMU86 -91	MHAD 101-v	80-pair
TCD [1]	08.5	24.1	19.3	21.5
S-SDTW [2]	35.9	16.1	37.7	21.6
U-SDTW [2]	35.1	16.1	35.5	25.6
S-EVACO	59.4	57.5	56.2	64.5
U-EVACO	50.3	51.0	45.9	54.2
Guo et.al [3]	-	-	-	51.6

