Subspace Clustering for Action Recognition with Covariance Representations and Temporal Pruning

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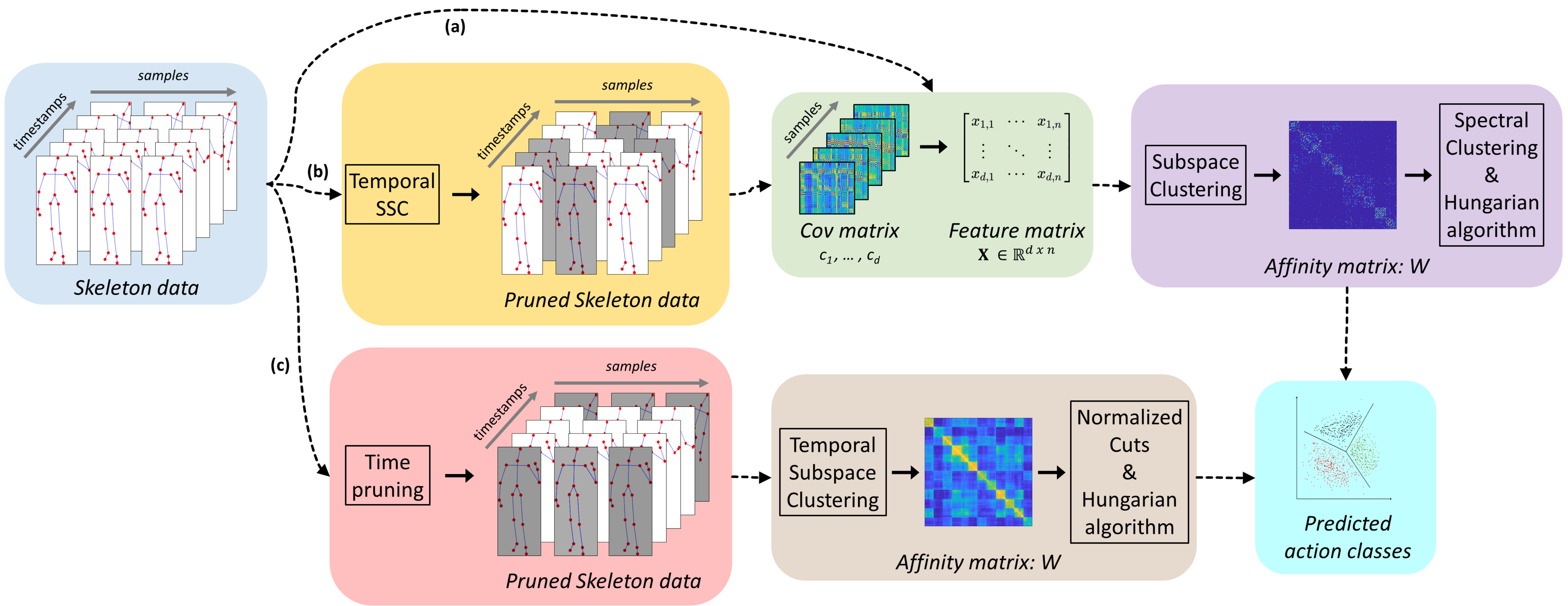
MOTIVATION

- *Unsupervised* Skeleton-based Human Action Recognition (HAR):
  - Classify human action sequences using subspace clustering and skeleton-joints datasets.
- **Subspace Clustering:**
  - High-dimensional data represented as a union of subspaces,
  - Lower dimensionality and simpler geometrical structure,
  - Each subspace corresponds to an action class.
- **Skeleton Joints Action Dataset:**
  - Multi-dimensional time series of human actions,
  - Free of background clutter, lighting conditions, variations on clothing,
  - Limitedly explored due to noisy data, missing joints, etc.

CONTRIBUTIONS

- **Subspace Clustering** on HAR:
  - **Skeleton-joints datasets** are used,
  - showing favorable unsupervised results as compared to *supervised* state of the art,
  - where *some unsupervised results outperform supervised state of the art*.
- **Temporal data heuristics:**
  - **Covariance** representations,
  - and **time-pruning strategies**,
  - to encode temporal length of skeleton data without compromising results.

PROPOSED METHOD



- Proposed computational pipeline**:**
  - 3 Temporal data heuristics (Covariance, Temporal, and Time-pruning Subspace Clustering),
  - Subspace Clustering to build Affinity Matrix [1-7],
  - Spectral Clustering or Normalized Cuts to generate the predicted action classes,
  - Hungarian Algorithm for overall accuracy.

- **Covariance Subspace Clustering:** representation method to encode datasets with different temporal length between each samples.
  - Flattening and vectorization by keeping diagonal and upper-triangular elements of covariance matrix,
  - Self-expressiveness based Subspace Clustering to build Affinity Matrix.

Dataset	Km	Sc	EDSC	OMP	DSCN	LSR	SSC	EnSC
F3D	45,58	66,05	54,42	61,40	57,02	60,47	69,12	**70,23**
UTK	34,67	66,83	52,71	58,79	69,35	57,79	73,97	**78,90**
MSRP	42,78	52,69	**51,90**	50,14	49,26	47,31	49,60	49,86
MSRA	41,11	65,17	52,69	43,99	59,91	54,40	57,27	**62,84**
G3D	31,22	64,71	44,48	45,70	62,59	64,25	65,16	**72,25**
HDM-05-14	32,36	53,35	52,42	47,67	**56,27**	51,60	49,13	**56,00**
HDM-05-65	31,41	44,46	**44,43**	36,07	30,95	42,98	35,98	42,38
MSRC	61,54	84,34	81,30	51,20	71,35	**87,04**	62,27	83,27

- **Temporal Subspace Clustering:** compress action sequence to a fixed length ϕ:
  - min ϕ : shortest temporal length by random permutation,
  - min TemporalSSC: shortest temporal length using Sparse Subspace Clustering [1],
  - Percentage TemporalSSC: ϕ as percentage value of sample's temporal length,
  - Threshold TemporalSSC: ϕ as threshold value of sample's temporal length.

Dataset	SSC	min ϕ	min temporalSSC	percentage temporalSSC	ϕ	threshold temporalSSC	ϕ
F3D	**69,12**	67,91	66,51	65,12	75%	68,84	50%
UTK	73,97	64,82	**80,90**	68,34	25%	72,86	75%
MSRP	49,60	48,88	47,88	**50,42**	25%	49,58	25%
MSRA	57,27	59,61	57,09	62,66	25%	**63,02**	75%
G3D	65,16	64,86	64,10	69,68	75%	**71,49**	75%
HDM-05-14	49,13	**63,12**	59,04	59,33	25%	59,77	25%
HDM-05-65	35,98	41,31	**44,00**	43,66	25%	41,53	50%
MSRC	62,27	**83.79**	83,62	83,41	75%	83,14	75%

- **Time-pruning Subspace Clustering:** compress action sequence to a fixed length ϕ with dictionary-based Subspace Clustering [2]:
  - TSC min: shortest temporal length by random permutation,
  - TSC max: longest temporal length by data replication,
  - temporalSC + TSC: shortest temporal length using Spectral Clustering,
  - temporalKM + TSC: shortest temporal length K-means Clustering.

Dataset	TSCmin	cov TSCmin	TSCmax	cov TSCmax	temporalSC + TSC	temporalSC + TSC cov	temporalKm + TSC	temporalKm + TSC cov	supervised s.o.t.a.
F3D	84,65	81,40	94,88	81,86	**95,81**	88,84	87,91	87,44	99,07
UTK	93,97	96,98	**99,50**	92,96	96,98	96,98	93,47	83,92	100,00
MSRP	93,48	81,30	**98,02**	84,70	88,67	76,20	96,32	71,10	95,50
MSRA	87,18	79,89	85,64	83,30	82,47	81,13	**88,51**	87,61	97,40
G3D	88,99	90,20	85,07	92,61	90,20	92,46	88,84	**92,91**	96,02
HDM-05-14	**89,80**	86,73	80,32	83,82	88,48	84,84	83,97	81,63	99,10
HDM-05-65	70,51	83,57	75,97	85,62	72,13	84,64	68,42	**86,00**	96,92
MSRC	97,96	91,09	**99,08**	99,05	98,81	97,42	99,00	91,07	98,50
AVG	88,32	86,40	89,81	87,99	89,19	87,81	88,31	85,21	
STD	7,79	5,59	8,62	5,72	8,18	7,05	8,80	6,31	

References:
[1] E. Elhamifar et al., *Sparse subspace clustering: Algorithm, theory, and applications*, IEEE TPAMI, 2013.
[2] S. Li et al., *Temporal subspace clustering for human motion segmentation*, ICCV, 2015.
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[4] C. You et al., *Scalable sparse subspace clustering by orthogonal matching pursuit*, CVPR, 2016.
[5] P. Ji et al., *Deep subspace clustering networks*, NIPS, 2017.
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[7] C. You et al., *Oracle based active set algorithm for scalable elastic net subspace clustering*, CVPR, 2016.

Code available!
https://github.com/IIT-PAVIS/subspace-clustering-action-recognition