

ABSTRACT

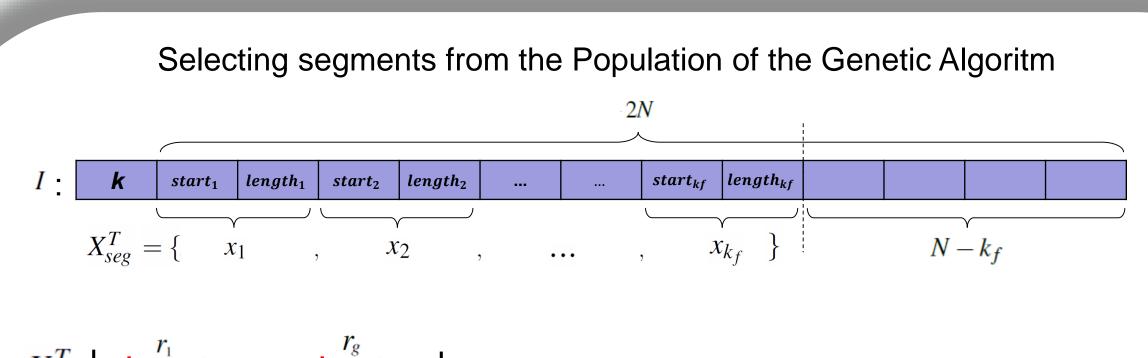
This paper introduces a framework for gesture and action recognition based on the evolution of temporal gesture primitives, or subgestures. Our work is inspired on the principle of producing genetic variations within a population of gesture subsequences, with the goal of obtaining a set of gesture units that enhance the generalization capability of standard gesture recognition approaches. In our context, gesture primitives are evolved over time using dynamic programming and generative models in order to recognize complex actions. In few generations, the proposed subgesture-based representation of actions and gestures outperforms the state of the art results on the MSRDaily3D and MSRAction3D datasets.

1. Motivation

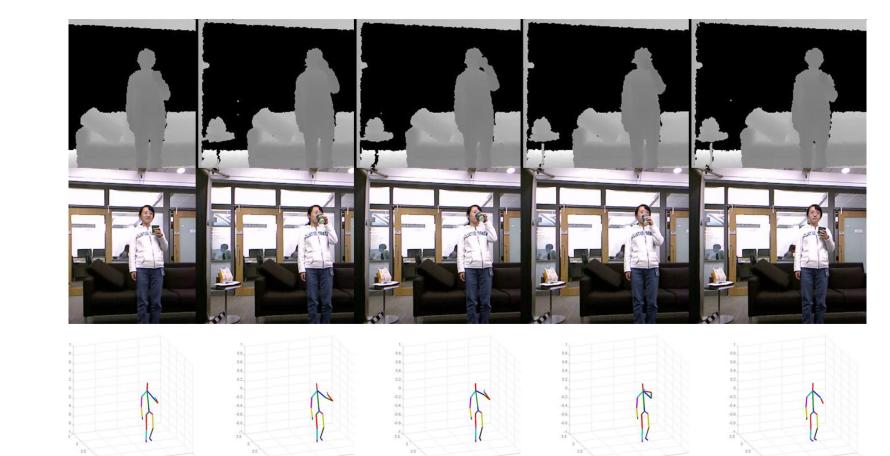
3. Data and Results

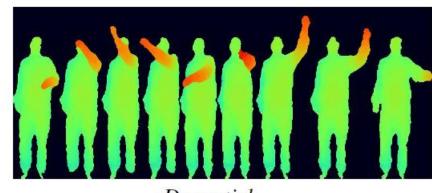
- Very recently, evolutionary algorithms have been also developed for key-frame (Bag of *Key Poses)* extraction [1-2].
- While these methods learn from a subset of frames, in *subgesture* modeling we aim at learning spatio-temporal units [3-6].
- Class-specific key poses/subgestures give a good performance. Nevertheless, we include the fact that there are inter-class subgestures that might be shared among different classes.
- •We evolve such gesture primitives integrated into a gesture recognition framework coupled with either *DTW* or *HMM*.

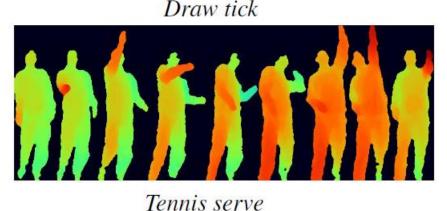
2. Framework Overview

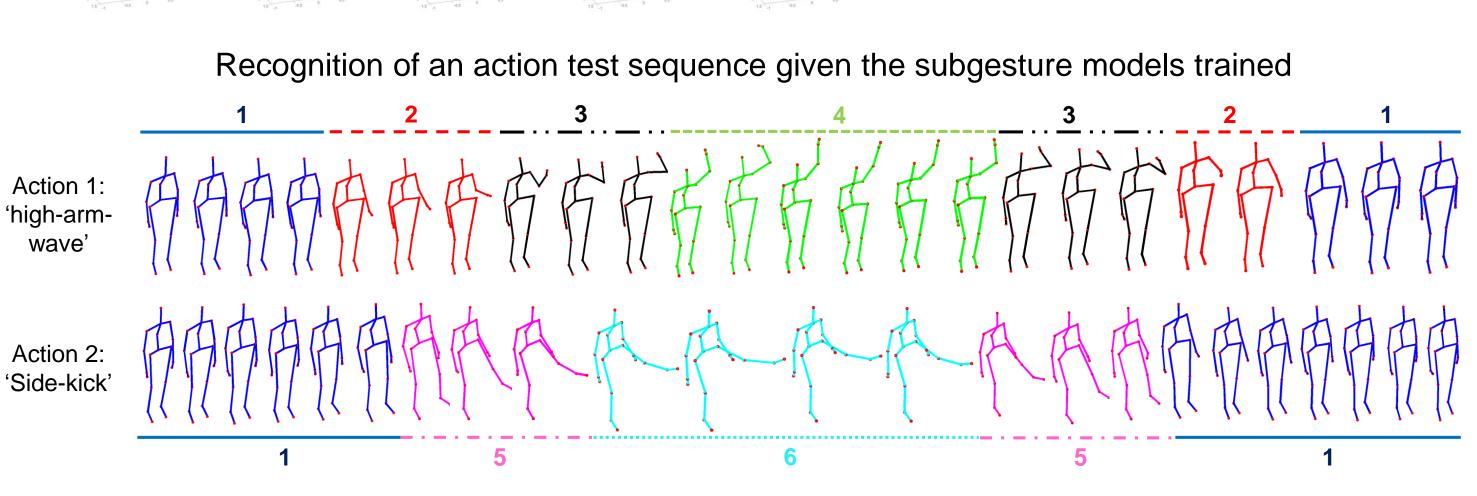


Examples of the MSR datasets

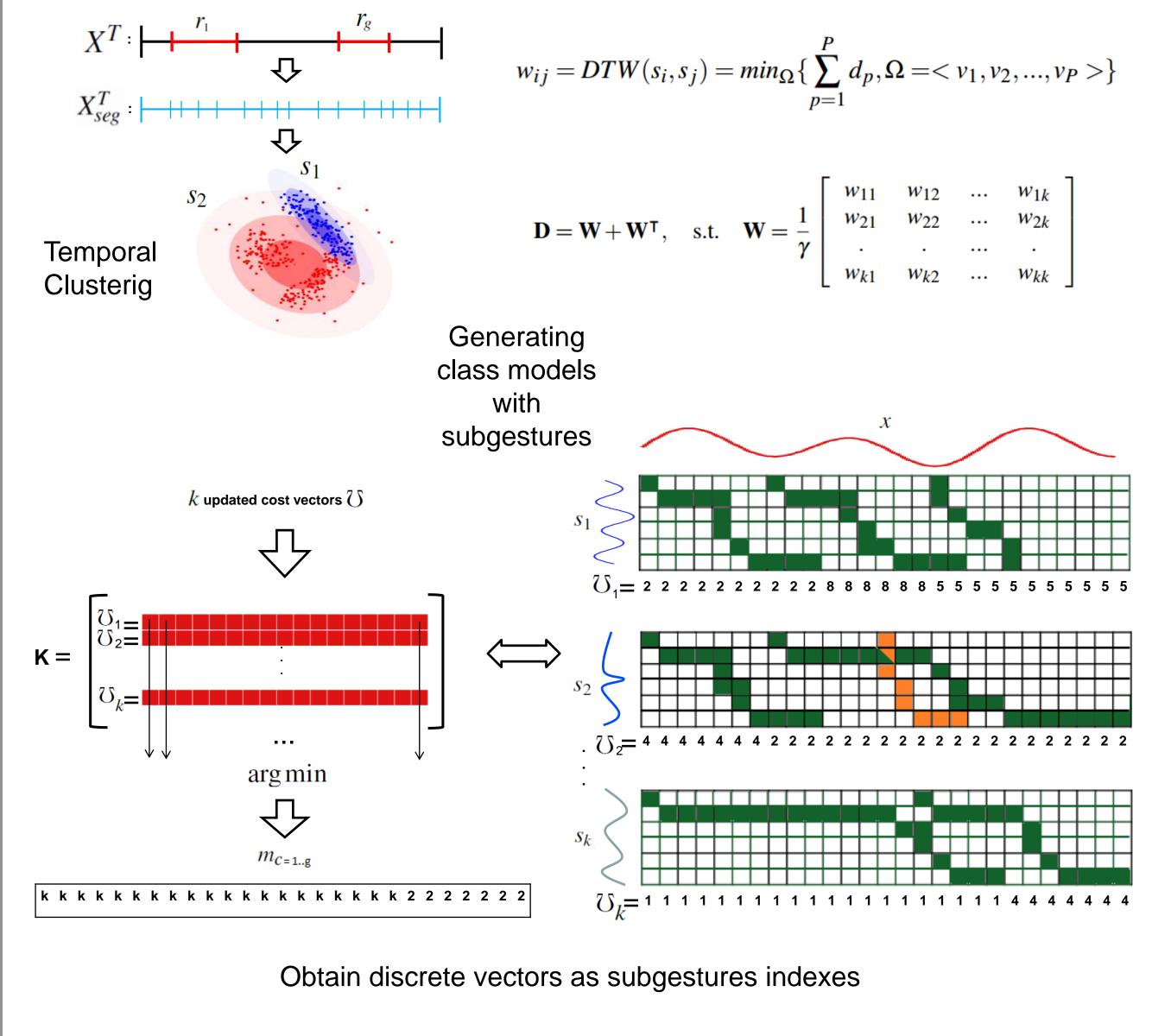


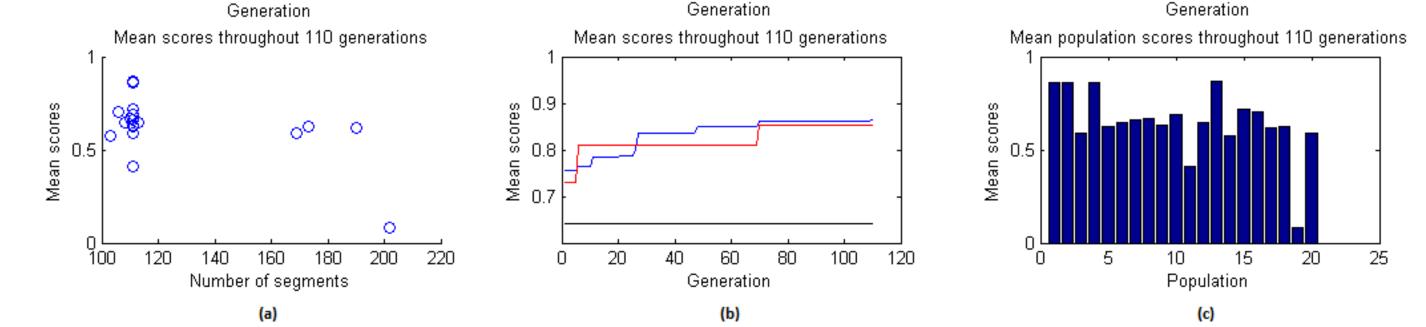






Evolution of the genetic algorithm for the first fold of the MSRDaily3D dataset. (a) Chosen number of segments; (b) Scores of the best individuals; (c) Scores of the population



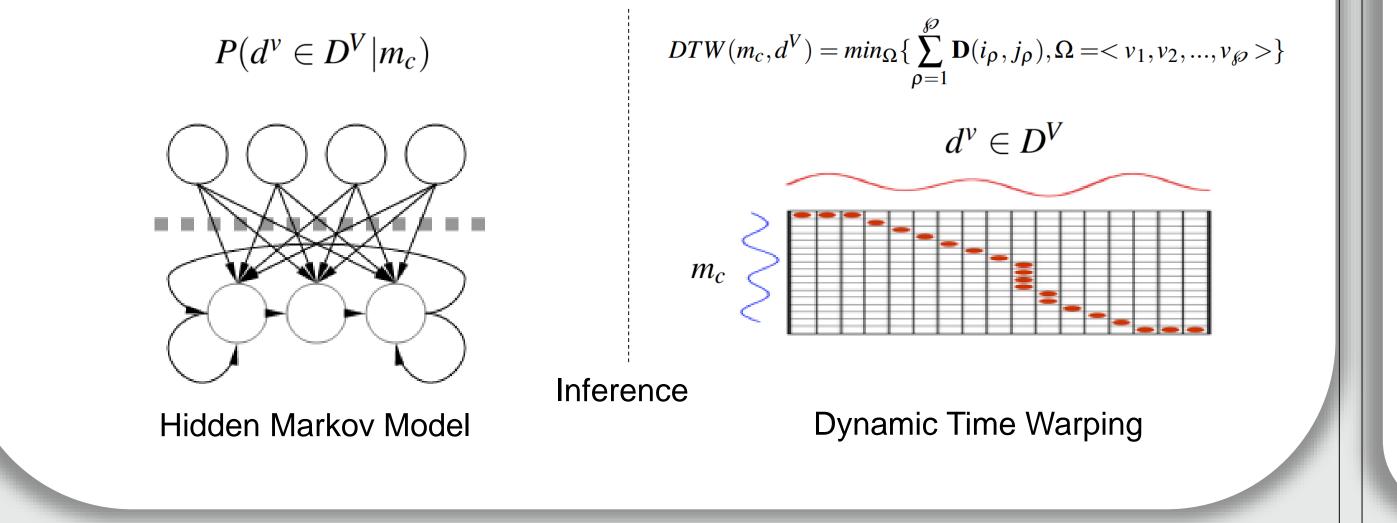


Quantitative results of the recognition accuracy both on the Half-Split and on the 5-fold cross validation

MSRAction3D-HS		MSRDaily3D-CV		MSRDaily3D-HS	
Method	Accuracy	Method	Accuracy	Method	Accuracy
[32] (LOP+J.)	88.2%	[11] (SOSVM)	68.3%	[31] (LOP)	42.5%
[35] (DCSF)	89.3%	[12] (SMMED)	73.20%	[21] (DTW)	54%
[24] (HOPC)	91.64%	[35] (DCSF)	83.60%	[32] (MKL)	80.0%
[7] (PBR)	92.3%	[35] (DCSF+Skl.)	88.2	[16] (GP)	85.6%
[30] (MMTW)	92.7%	-	-	[32] (LOP+J.)	85.75%
		Dynamic Time Wa	arping		
Baseline	85.76%	Baseline	77.36%	Baseline	70.20%
Evolved	90.89%	Evolved	89.51 %	Evolved	88.16%
		Hidden Markov M	Iodel		-
Baseline	70.85%	Baseline	74.62%	Baseline	69.29%
Evolved	95%	Evolved	91.39%	Evolved	92.30%

4. Conclusion

• We introduce a novel approach for learning dynamic gesture primitives for gesture and action recognition.



• An evolutionary computing framework is presented, which incorporates two most notable gesture recognition methodologies, namely DTW and HMMs.

• Experimental results show the competitiveness of our methods, outperforming state of the art results in benchmark data sets after few generations

• Proposed subgesture learning methodology enhances the recognition performance of traditional techniques.

• Future work includes extending the framework for related tasks (e.g. gesture spotting, event detection) and an extensive evaluation under different parameter settings.

References

[1] A.A. Chaaraoui and F. Florez-Revuelta. Adaptive human action recognition with an evolving bag of key poses. IEEE Transactions on Autonomous Mental Development, 6(2):139–152, 2014.

[2] H.J. Escalante, J. Martinez, S. Escalera, V. Ponce-López, and X. Baró. Improving the bag of visual words with genetic programming. In IJCNN, 2015.

[3] K. Li, J. Hu, and Y. Fu. Modeling complex temporal composition of actionlets for activity prediction. In ECCV, volume 7572, pages 286–299, 2012

[4] M. R. Malgireddy, I. Nwogu, S. Ghosh, and V. Govindaraju. A shared parameter model for gesture and sub-gesture analysis. In Combinatorial Image Analysis, volume 6636, pages 483–493, 2011.

[5] V. Ponce, M. Gorga, X. Baro, and S. Escalera. Human behavior analysis from video data using bag-of-gestures. In IJCAI, 2011.

[6] L. Wang, Y. Qiao, , and X. Tang. Video action detection with relational dynamic-poselets. In ECCV, 2014.