Late Fusion of Bayesian and Convolutional models for Action Recognition

Camille Maurice¹, Francisco Madrigal¹ et Frédéric Lerasle¹² ¹LAAS-CNRS, ²University Paul Sabatier, Toulouse - contact: cmaurice@laas.fr

Problem Definition and Contributions

• Goal

• To **recognize actions** on videos where a person performs several sequential actions with objects.

• Our Contributions

- Addition of **recurrent layer** to a 3D CNN to take into account action transitions
- A hybrid approach based on late fusion

Key Statements

- A Bayesian approach with great results on **specific** actions
- A **possible synergy** between a deep-learning and Bayesian approaches
- **Temporal consistency** within an action and throughout the sequence
- Action sequences importance to **leverage ambiguities** thus improve performances

Problem Definition and Contributions

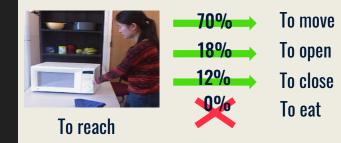
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Models Characteristics

• Bayesian Model (ANBM) [1]

ANBM

C3D

- Models skeletons, skeletons-objects and object-object interactions in a joint probability
- Models action transitions
- C3D [5]
 - 3D convolutions to learn spatio-temporal features on video clips
 - Does not model action transitions

[1] A new Bayesian Model for Action Recognition, C. Maurice *et al.*[5] Learning spatiotemporal features with 3d convolutional networks, D. Tran *et al.*

C3D-GRU

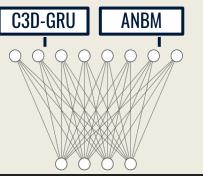
• C3D-GRU

- Recurrent layer with **memory** cell to capture time dependencies
- Gated Recurrent Unit, a recurrent layer suitable for **short sequences**
- Freeze C3D weights, then train the
 GRU layer with 2 successive clips as input



Late Fusion with a Dense Layer

- Predictions concatenation
- Connection to a **fully-connected** layer with **soft-max** activation
- Enable a **late fusion** with correlations between predictions

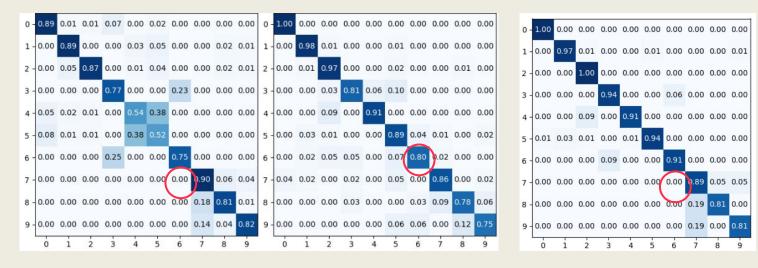


Dataset	Approaches	Accur acy	
CAD-120	GEPHAPP[2]	79.4	
	ANBM[1]	82.2	
	GPNN[3]	87.3	
	Ours	86.1	
Watch-n-Patch	PoT[4]	49.9	
	ANBM[1]	76.4	
	GEPHAPP[2]	84.8	
	Ours	93.0	

Results

• 2 public datasets

Results



C3D-GRU

FUSION

ANBM

Conclusion and Future Works

Acknowledgements

- Performance gain, particularly in **under-represented** classes
- Performance gain when the sources of error are different

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