ICCV 2021 Workshop - SRVU

Spatio-Temporal Video Representation Learning for AI Based Video Playback Style Prediction

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Agenda

1) The Relevance of Video understanding for Mobile Devices
2) Current State of Video understanding approaches
3) Motion patterns in human action videos - mHMDB51 dataset
    a) Motion Type Classifier Architecture
    b) Quantitative Results
    c) Video playback style recommendation
4) Conclusion

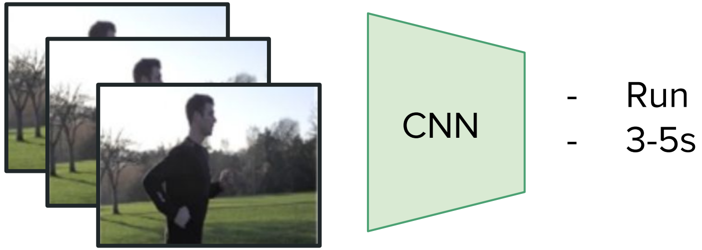
Video Analysis on Mobile Devices

- A large number of videos are captured on mobile phones each day that are shared various short video platforms like tik-tok, snapchat, reels.
- In current scenario there are a range of tools available where the user has to manually select and try of the filters
- Their is a necessity of automated tools to edit the videos on mobile devices to make them more shareable
- Intelligence capability for mobile devices

[1] Best Short Video Apps for Socializing 2021
https://www.apowersoft.com/best-short-video-apps.html

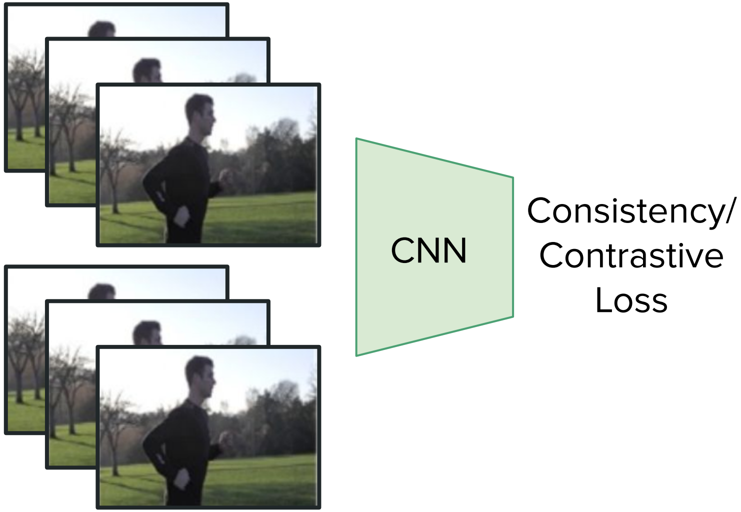
Current State of Video Understanding

Action recognition and localization



- Training with large scale labeled datasets
- Supervised Training with 3D CNNs

Unsupervised representation learning



- Training with unlabelled data to learn spatio-temporal representations

Motion Classification

Every common world human actions can be categorized into one of the following five primitive motion type classes: linear, projectile, oscillatory, local and random - mHMDB51

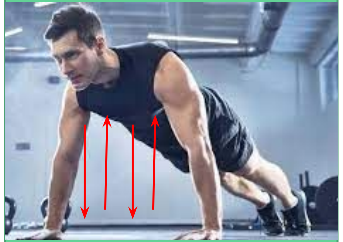
Linear

Ex. Run, Walk, Brush-hair, Climb, Push, Pull

Projectile

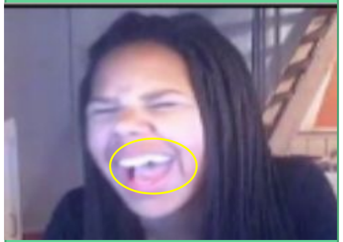
Ex. Shoot ball, Cartwheel, Dive, Jump, Golf

Oscillatory



Ex. Pushups, Dribble, Situps, Clap

Local



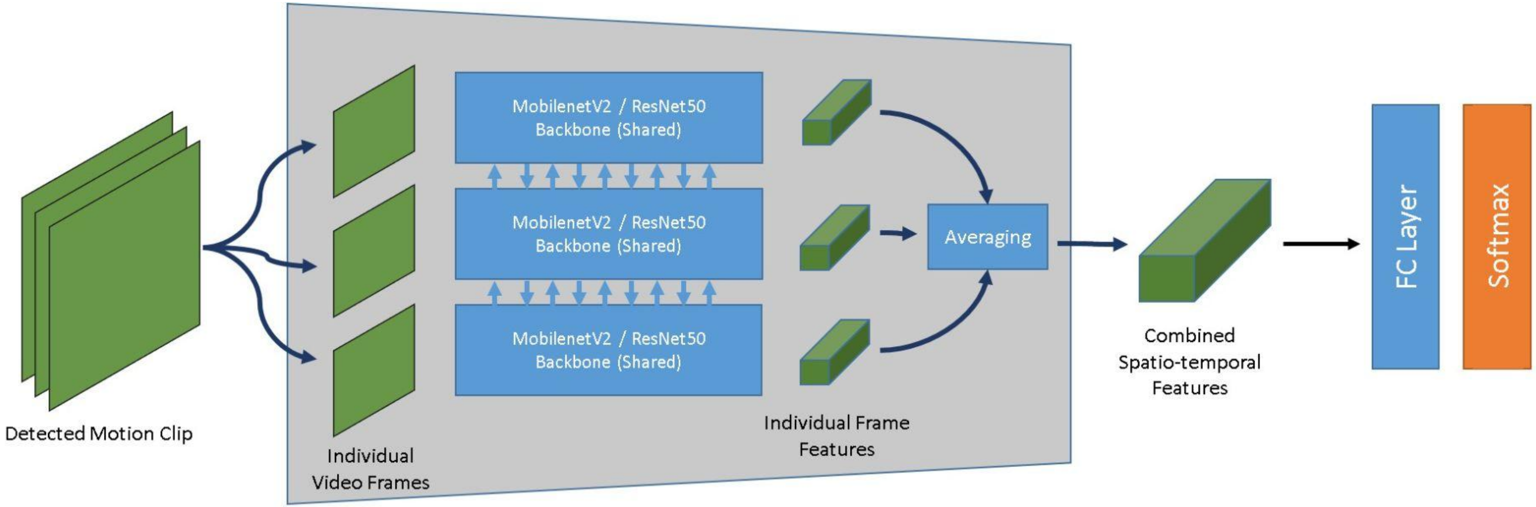
Ex. Smile, Chew, Talk, Smoke, Shake-hands

Random

Ex. Fencing, Fall, Sit, Stand, Hug

Motion Classifier Architecture

- Our model architecture is inspired by Temporal Segment Networks with TSM blocks
- We sample T frames from the video and process them through a MobileNet based TSN backbone



- Linear
- Projectile
- Oscillatory
- Local
- Random

[1] Temporal Segment Networks: Towards Good Practices for Deep Action Recognition
https://arxiv.org/abs/1608.00859

Motion Classification Results

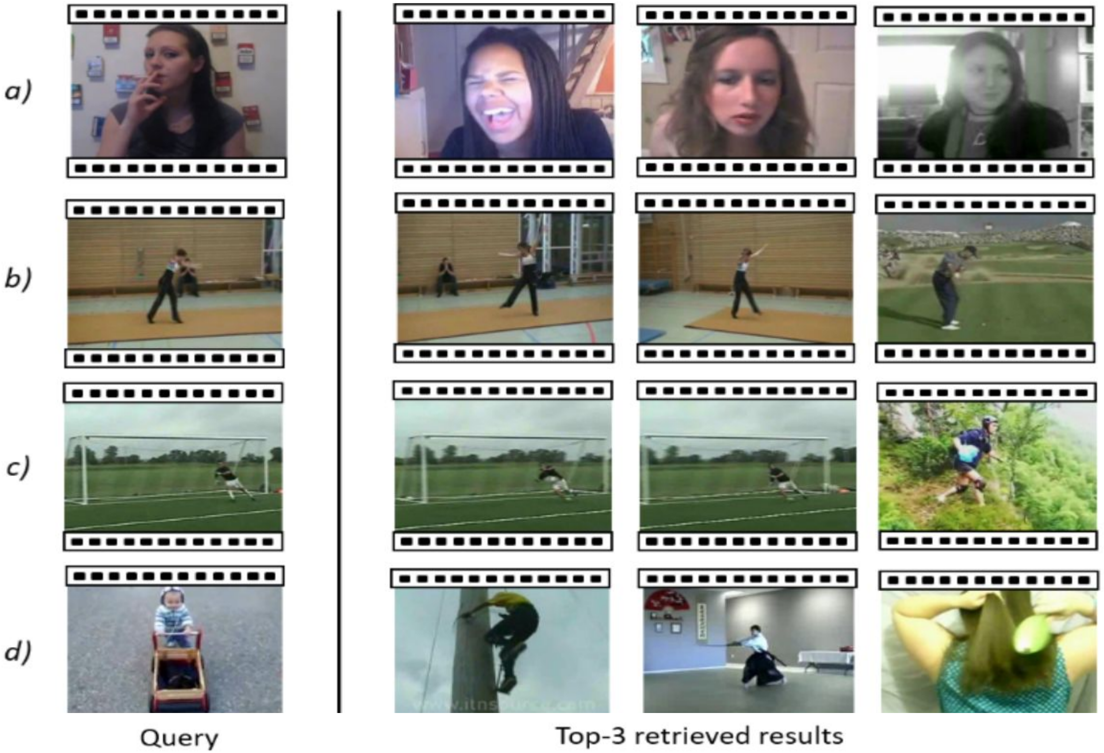
Table1. Model Performance Comparison

Method	Accuracy
Flow Baseline Classifier	25.64
$\text{Ours}_{\text{Scratch}}$	38.56
$\text{Ours}_{\text{ImageNet}}$	57.58
$\text{Ours}_{\text{Kinetics}}$	72.68

Table2. Ablation on number of input frames

Segments	Accuracy	MACs
1	61.76	0.41G
2	71.05	0.82G
3	72.68	1.23G
8	68.17	3.28G

Results on the Downstream Task of Video Retrieval



Video Playback Style Recommendation

Input Video Clip	Motion Type Predicted	Playback Style Assigned
Jogging 	***Linear***	*Reverse*
Diving 	***Projectile***	*Boomerang*
Drinking 	***Local***	*Loop*
Fencing 	***Random***	*Forward*

Conclusions

- A novel direction for video understanding by motion type classification
- Inference time of 200ms for a 10s video clip on a Samsung S20 phone
- Learned rich motion representations that generalize well to downstream task of video retrieval
- An application of Video Playback style recommendation system based on predicted motion type classification