DeViQ – A deep no reference video quality model

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Motivation

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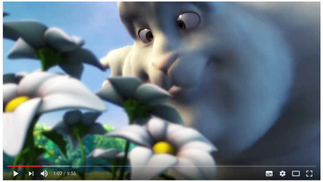 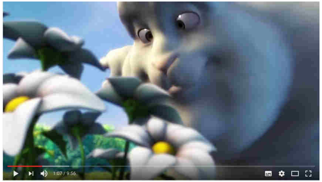 

- most internet traffic generated via video streaming providers [4]
- user's expectation: best possible video quality under every condition
- trending technologies: **4k/UHD**, HDR, 360 degree, encoders, ...
- automated monitoring/optimization of perceived video quality

→ a brief look on current pixel based video/image quality models

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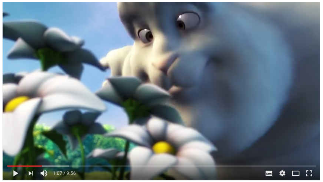

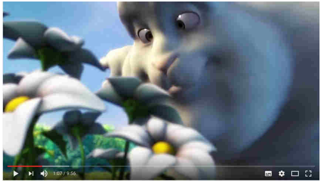

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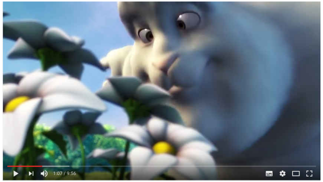

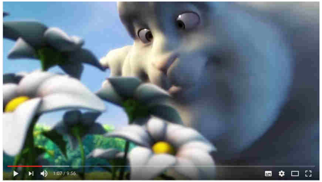

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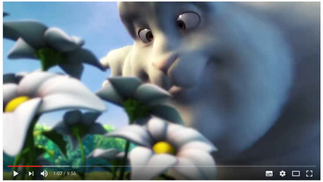

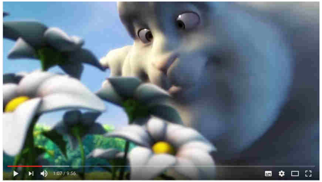

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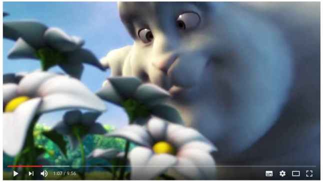

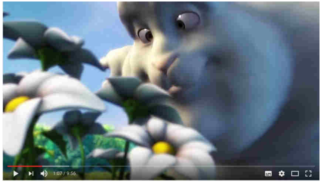

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Video/image quality models

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- full-reference models highly accurate to human perception [18]
  - e.g. Netflix's VMAF [14] → **reference video**
- hand-crafted features [12, 14]
  - new encoders/ technologies → new artefacts → **new features**
- models using deep neural networks [3, 11, 8, 5, 6, 9]
  - patching to reduce input size → **losses global connections; many patches for 4K**
  - training requires per frame quality scores → **huge database**

→ ideas for solving the identified research problems

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How to solve the identified problems?

- huge training database for no-reference model:
  - generate ground-truth per frame data from full-reference model: VMAF [14, 10]
- hand-crafted features
  - using a pre-trained DNN for automatic feature extraction: inception-v3 [17]
- patching and global connection; many patches for 4K resolution
  - using hierarchical sub-images with larger block size: 299x299

→ introduce our model DeViQ (**De**ep **Vi**deo **Q**uality)

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DeViQ– General approach

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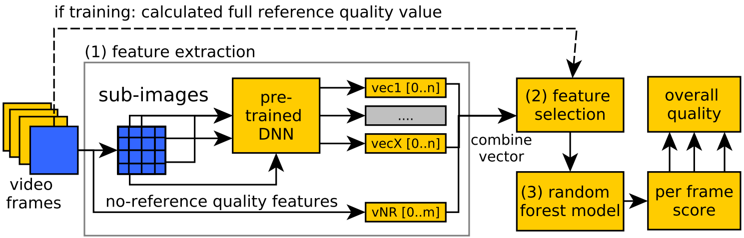

- (1) automatic feature extraction
  - pre-trained classification DNN
  - hierarchical sub-images: full, 1/2 of each dimension, 1/4 and 1/8 = 85 images
  - no-reference features; brisque+niqe [12, 13]
- (3) random forest model with (2) feature selection
- final quality score: mean value of each frame

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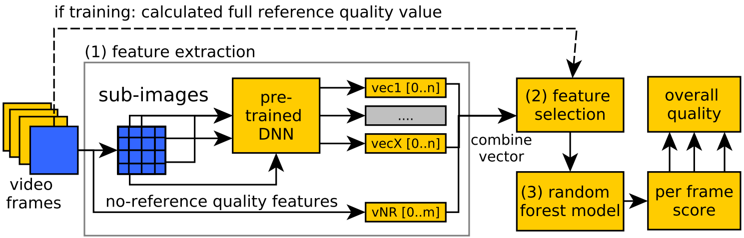

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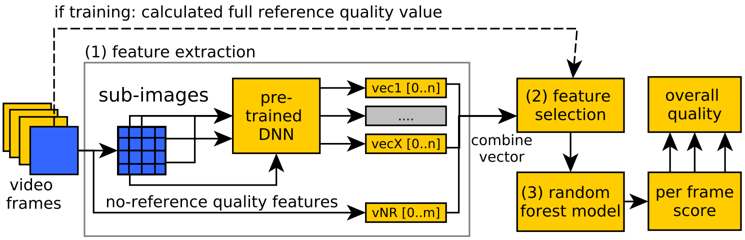

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DeViQ – Evaluation – Dataset – Source Sequences

all source videos: UHD-I (3840x2160); 60 fps (except sintel*); 10 s

train


harmonic [7]


blender [2]*


TUIL


TUIL

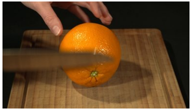

Sony [15]


Netflix

validation


harmonic [7]


blender [1]


TUIL


TUIL

Sony [16]


Netflix

DeViQ – Evaluation – Conditions

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- 3 codecs; 5 resolutions; 2/3 bitrates per resolution
- $\rightarrow$ encoded to 320 videos: **train=50%; validation=50%; no overlapp**
- calculated VMAF scores for $\approx 200k$ **frames**
- for validation: subjective test (22 participants; avg. age=26.7)
- comparison to retrained brisque+niqe model/ full-reference metrics

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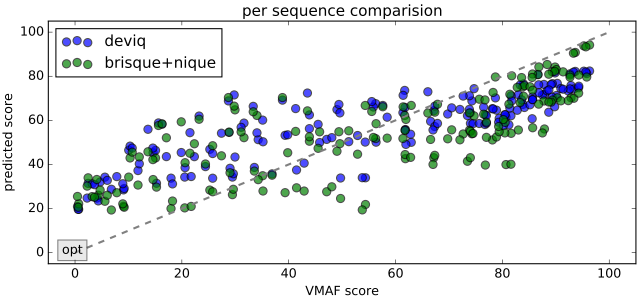
DeViQ – Evaluation – Prediction vs. VMAF

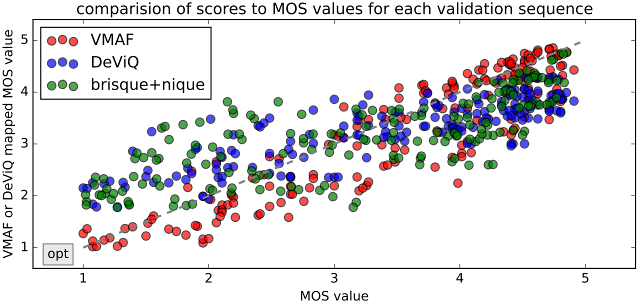
average VMAF-scores with DeViQ and brisque+niqe predictions



method	*RMSE*	R^2	pearson	kendall	spearman
deviq	18.87	0.60	0.84	0.66	0.84
brisque+nique	19.75	0.56	0.85	0.64	0.83
vifp	22.28	0.44	0.58	0.46	0.63

DeViQ – Evaluation – Prediction vs. MOS

comparison of VMAF, DeViQ, brisque+niqe to MOS values



method	$RMSE$	R^2	kendall	pearson	spearman
vmaf	0.55	0.76	0.72	0.92	0.89
deviq	0.70	0.61	0.61	0.84	0.81
brisque+nique	0.81	0.47	0.53	0.75	0.73
vifp	0.86	0.41	0.52	0.70	0.67

Conclusion and Future Work

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- identified main problems: hand-crafted features; patching; huge database $\rightarrow$ DeViQ (**De**ep **Vi**deo **Q**uality)
  - $\rightarrow$ performs good compared to full-reference, no-reference models
- open points:
  - frame and sub-image selection
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...... are there any questions?

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deviq,brisque+nique vs. vmaf

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msssim	48.99	-1.70	0.54	0.46	0.63
ssim	49.88	-1.80	0.48	0.44	0.60
psnrhvs	56.09	-2.55	0.33	0.52	0.72

deviq,brisque+nique,vmaf vs. mos

method	$RMSE$	R^2	cohen_d	kendall	pearson	spearman
vmaf	0.55	0.76	0.24	0.72	0.92	0.89
deviq	0.70	0.61	0.19	0.61	0.84	0.81
brisque+nique	0.81	0.47	0.34	0.53	0.75	0.73
vifp	0.86	0.41	-0.34	0.52	0.70	0.67
msssim	1.70	-1.32	-1.72	0.46	0.69	0.61
ssim	1.74	-1.42	-1.76	0.45	0.65	0.60
psnrhvs	2.27	-3.15	0.30	0.60	0.34	0.76

feature importance

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for each 1000 feature values we summed the feature importance of our model; subimage 85=no-reference features