Impacts of Video and Encoding Parameters on the Encoding Energy

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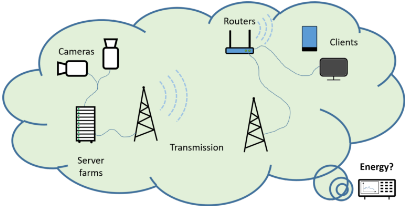
Motivation

- Global significance of energy consumption of the video coding systems
  - 1% of global greenhouse gas emissions (2018) [5]
  - 80% of IP traffic is video data [2]
  - Example: Youtube [1]
    - 300 hours new video materials per minute
    - Uploaded in arbitrary compression formats
    - Transcoded into a proprietary format
    - Different transmission channels with different transmission rates
    - Huge server farms - to perform the encoding

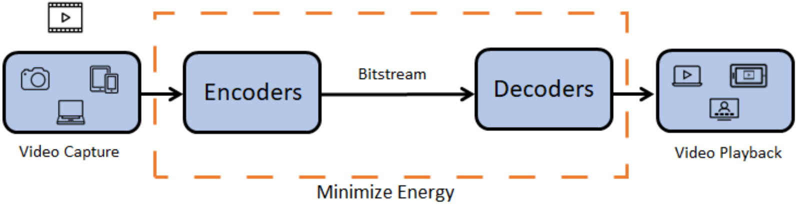


Motivation

- Limited battery life of portable devices
  - Portable devices $\rightarrow$ record videos, store them, upload them to the Internet, or play them back and video streaming $\rightarrow$ video coding is a necessary step
  - Less energy consumption $\rightarrow$ extend the battery life of portable devices.
  - Example: Typical coder for AVC [4]:
    - Average power: 7 W
    - Medium quality and relatively low resolution
    - Typical smartphone battery $\rightarrow$ empty $\approx$ 2 hours

Energy-efficient video communication is critical and globally significant.

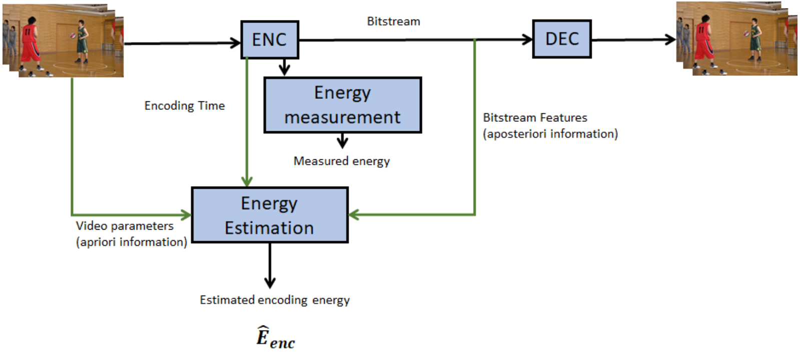
Motivation



Goal: Energy-rate-distortion optimization

- Decoding-energy-rate-distortion optimization [3]
- **Encoding-energy-rate-distortion optimization**

Motivation



- How do the encoding energy energy change with respect to to encoding and video features?
- Is it possible to obtain valid encoding energy estimates using encoding and video features?

Outline

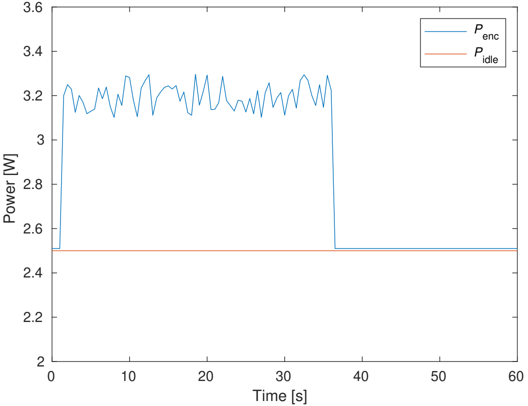
- Motivation
- Energy Measurement Setup
- Impact of Encoding Parameters on Encoding Energy
- Impact of Video parameters on Encoding Energy
- Conclusion & Outlook

Energy Measurement Setup

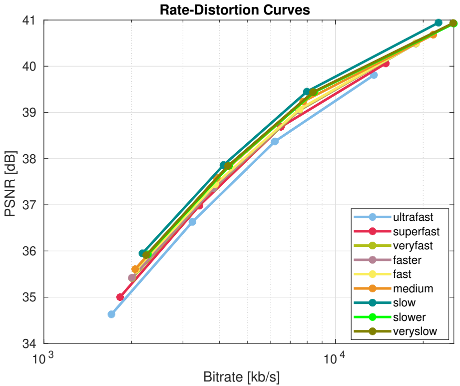
- Codec: HEVC, Software encoding process, encoder: x265
- Two consecutive measurements

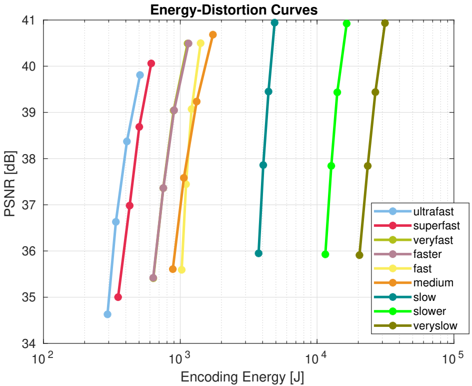
$$E_{\text{enc}} = \int_{t=0}^{T} P_{\text{total}}(t)\mathrm{d}t - \int_{t=0}^{T} P_{\text{idle}}(t)\mathrm{d}t$$

- Intel CPU - Integrated power meter - Running Average Power Limit (RAPL)
- Repetition of measurements
- Confidence interval test



Rate- and Energy-distortion Curves

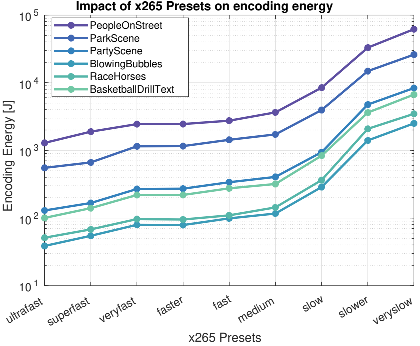




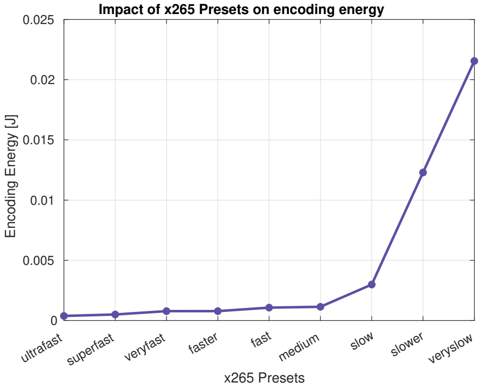
Example: BasketballDrive

Preset

- Optimize the trade-off between encoding speed and compression efficiency
- Employ different coding features and its combinations
- 9 x265 presets are evaluated
- Faster presets: at the expense of quality and compression efficiency → consumes less energy
- Slower presets: encoder tests more encoding options → achieve the lowest bit rate at the selected quality → consumes more energy



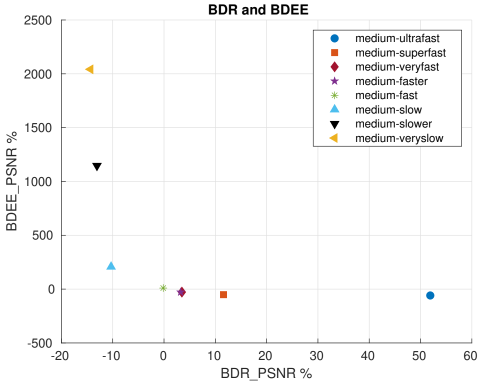
Preset



Preset	Relative Diff (%)
ultrafast	0
superfast	0.98
veryfast	2.26
faster	0.01
fast	2.35
medium	0.56
slow	15.04
slower	75.66
veryslow	75.29

Average of all sequences, CRF=18, Energy normalized wrt resolution

Preset

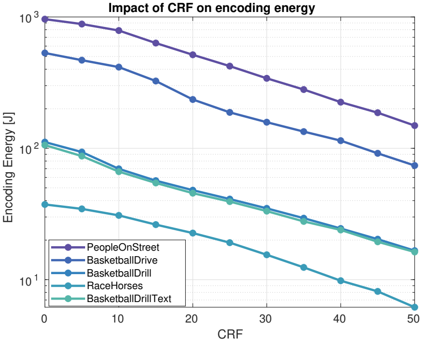


Preset	BDR	BDEE
ultrafast	51.8994	-59.1178
superfast	11.5972	-51.4557
veryfast	3.4878	-27.7379
faster	3.2378	-27.7435
fast	-0.14815	9.8436
slow	-10.3175	207.2988
slower	-13.0689	1146.1795
veryslow	-14.3295	2041.9881

Average BD values, medium preset as reference

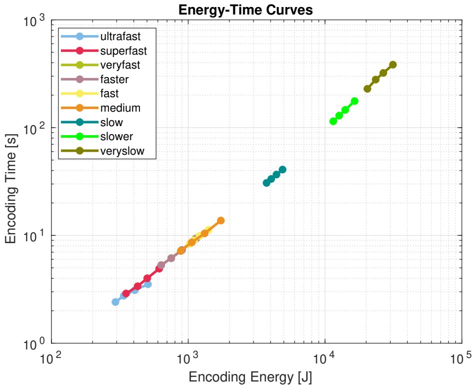
CRF

- Quality and rate control setting for the x265 encoder
- Encoder adjusts the QP → achieve chosen quality level
- Lower CRF values → better quality at the expense of a higher bitrate → consumes more energy
- Higher CRF values → mean more compression → noticeable quality degradation → consumes less energy
- 11 CRF values are evaluated: 0:5:50

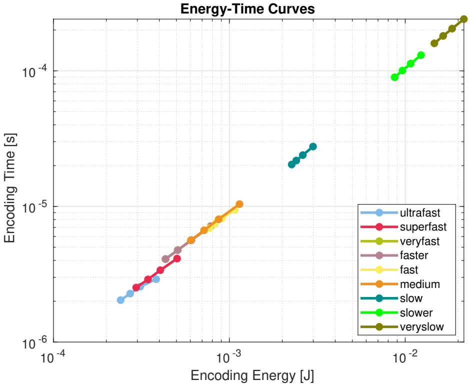


Encoding Time

Energy to encode a sequence grows linearly with the encoder processing time



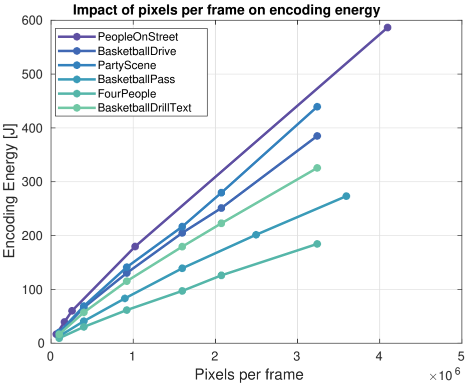
Example: BasketballDrive



Average, energy and time normalized wrt resolution

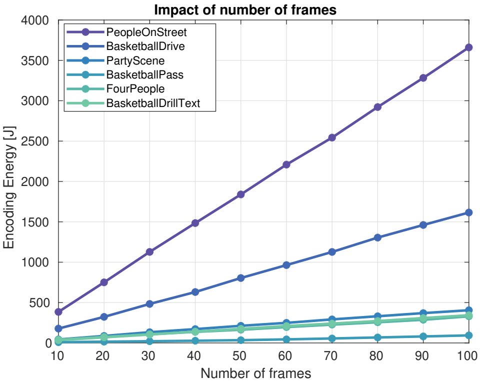
Resolution

- Video bit streams: coded with a medium preset, fixed number frames and a fixed CRF.
- Downsample and upsample: bi-cubic interpolation
- Energy to encode a sequence grows linearly with the number of pixels to be encoded.
- Slope and offset - depends on content

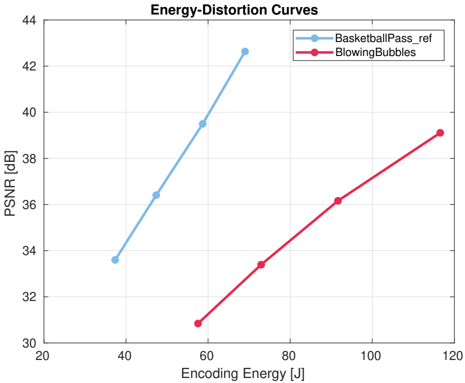


Number of Frames

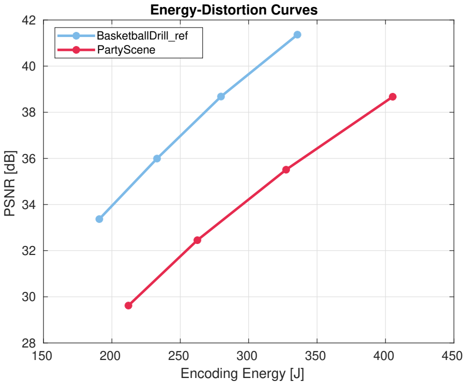
- Video bit streams: coded with a medium preset, and a fixed CRF.
- Energy to encode a sequence grows linearly with the number of frames to be encoded.
- Slope and offset - depends on the resolution and content



Content



$$\text{BDEE} = 98.60\%$$



$$\text{BDEE} = 45.59\%$$

Conclusion & Outlook

- Relations between encoding and video and encoding parameters
- Linear relation between encoding time and encoding energy suggests → the minimization of the encoding time → the minimization of the processing energy → identifying energy-efficient configurations
- Exhibits linear relation between resolution, number of frames with encoding energy
- Suggests feasibility of obtaining valid encoding energy estimates these features

Simple encoding energy estimation model

Encoding time of a lightweight encoding process → encoding energy of complex encoding configurations

Bibliography I

[1] Tech. rep. accessed 2018-08. 2018.

[2] Cisco Systems, Inc. *Cisco Annual Internet Report (2018-2023)*. https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.pdf. Mar. 2020.

[3] C. Herglotz, A. Heindel, and A. Kaup. "Decoding-Energy-Rate-Distortion Optimization for Video Coding". In: *IEEE Transactions on Circuits and Systems for Video Technology* 29.1 (2019), pp. 171–182. DOI: 10.1109/TCSVT.2017.2771819.

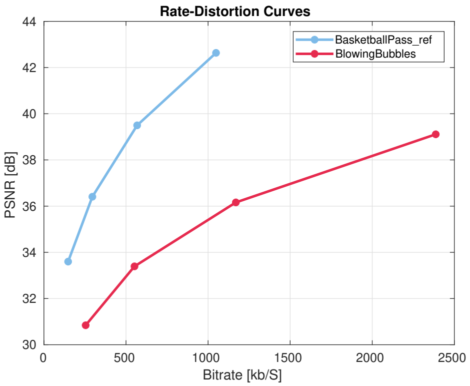
[4] Y. O. Sharrab and N. J. Sarhan. "Aggregate Power Consumption Modeling of Live Video Streaming Systems". In: *Proceedings of the 4th ACM Multimedia Systems Conference*. MMSys '13. Oslo, Norway: Association for Computing Machinery, 2013, pp. 60–71.

[5] The Shift Project. *Climate Crisis: The Unsustainable Use of Online Video*. Tech. rep. 2019.

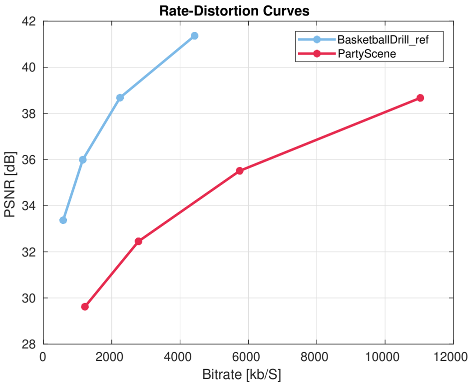
Thank You!

Thank You!

Backup



$$\mathrm{BDR} = 322.85\%$$



$$\mathrm{BDR} = 451.85\%$$