Video Quality (to be reviewed)

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Artificial Intelligence & Information Analysis Lab

Video Quality

- **Video Quality Assessment Methods**
- Subjective Quality Assessment
  - MOS and DMOS
  - Preference factor (PF)
- Objective Quality Assessment Metrics
  - Psychophysical Metrics
  - Engineering Metrics and Methods
  - PEVQ
  - Pixel – based Metrics
  - VMAF
- Camera image quality

Video

- A time-changing picture, whose spatial luminous intensities change over time [PIT2010].
- A three-dimensional space-time signal, sometimes called as moving/motion image [PIT2010].
  - The moving image is the image of a moving object or scene illuminated by a radiant source via a stationary or animated camcorder [VQA2018].

Video Quality Assessment

- The moving image is the image of a moving object or scene illuminated by a radiant source via a stationary or animated camcorder.
- To record the image we need the light source, the object and the video camera.
- In the case of the moving image, the time changes in the three – dimensional scene occur usually due to camera movement.

Video Quality Assessment

- Thus, time – varying images reflect the projection of three – dimensional moving objects on the image level, as a function of time.
- Digital video corresponds to a spatial – temporal sampling of this time – varying image.

Video Quality Assessment – Methods

Video Quality Assessment methods are the same as those used in Image Quality Assessment:

- Subjective Quality Assessment
- Objective Quality Assessment

Video Quality Assessment – Methods

We can see how these methods can be categorized as displayed in Figure 1 [REN2014].

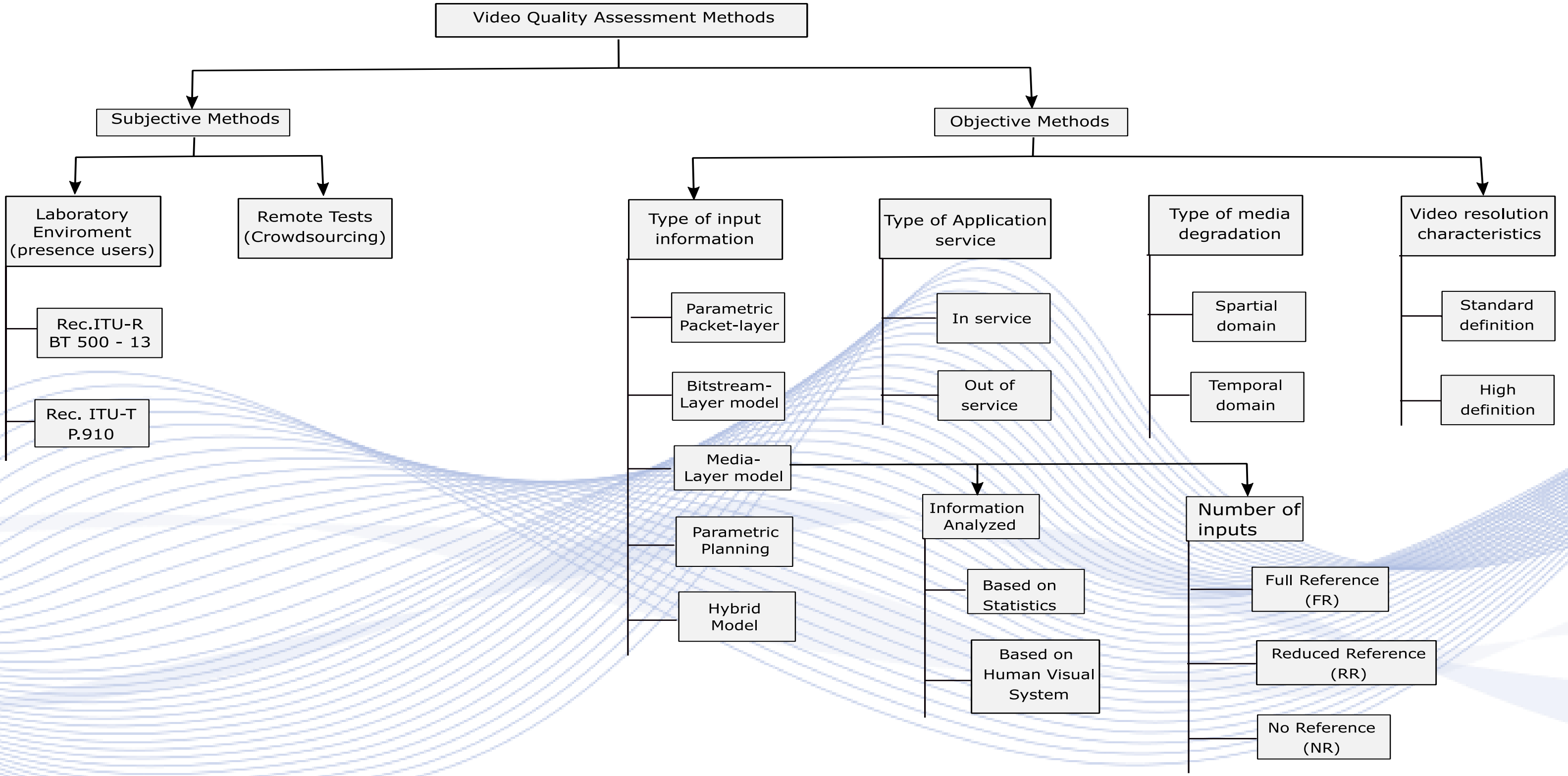

Fig.1 Classification of Video Quality Assessment Methods using different criterions.

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Subjective Quality Assessment

In addition to the Single – stimulus and Double – stimulus methods that are used in the Subjective method of Image Quality Assessment, there is also a third method [VQA2014]:

- Multi – stimulus: The subject rates the quality between several test videos including reference and hidden reference.
  - E.g. Subjective Assessment of Multimedia Video Quality (SAMVIQ)

MOS and DMOS

- The outcomes of a subjective experiment are used to compute Mean Opinion Score (MOS) or Differential Mean Opinion Score (DMOS).
- MOS and DMOS are used as input for the development of different objective quality metrics [VQA2014].
- **MOS and DMOS difference** [VQA2014] **:**

  MOS is the outcome when the subject rates a stimulus in isolation.

  DMOS is the outcome when the subject rates the change in quality between two versions of the same stimulus.

Preference factor (PF)

In video streaming service, the user's Quality of Experience (QoE) is related to video signal quality received at consumer's devices and the users' subjectivity. Here, the method in video quality assessment that is going to be analyzed is connected with the preference of a person into a specific video content type. [REN2014]

Preference Factor (PF) has to do with the human subjective opinion and preference and it is a function that works as a correction factor, because it adjusts the MOS index scores obtained by an objective metric, so it can improve the correlation with the real user's QoE. [REN2014]

Preference factor (PF)

Experimental results of subjective tests showed that PF values depend on [REN2014]:

- Human's preference, which could be, preference or no preference,
- Video content type that are classified into three kind of types: sport, documentary and news,
- Score level of MOS index values.

Preference factor (PF)

- **User's preference**:

Variables r_{p_i} and r_{np_i} are defined and represent the analogies between MOS scores estimated by users with and without preference. e is for preference and n is for mean and m is for mos and o is for no-preference.

$$r_{p_i} = \frac{m_i^e}{m_i^n}$$

$$r_{np_i} = \frac{m_i^o}{m_i^n}$$

where m_i^n is the mean value considering the total number of users with and without preference for the video test number i.

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Preference factor (PF)

- Video content:

A function named pf_e^{ct} that represents the PF function based on the r_{p_i} values for each video content type where the ct index represents the content type of the video and is limited to sport, documentary and news, and the p index represents that the user prefers CT. This type is:

$$pf_e^{ct} = \alpha \ln\left(m_p^n\right) + \beta$$

Also, m_p^n values are in the range from 0.5 to 4.5. The next table, represents the values of pf_e^{ct} according to the content type of the video.

Preference factor (PF)

Video Content type (ct)	α	β
Sports	0.741	0.219
Documentary	0.466	0.284
News	0.452	0.352

Similarly, to determine a function that represents the r_{np_i} values called pf_o^{ct} is:

$$pf_o^{ct} = 2 - \alpha \ln\left(m_p^n\right) - \beta$$

Where, α and β are the values presented in the previous table.

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Preference factor (PF)

- MOS index:

Once the pf_e^{ct} and pf_o^{ct} functions are defined, they can be used in different video streaming services, in which the m_p^n variable is replaced in those functions for the MOS index obtained by an objective metric as shown in Fig. 2.

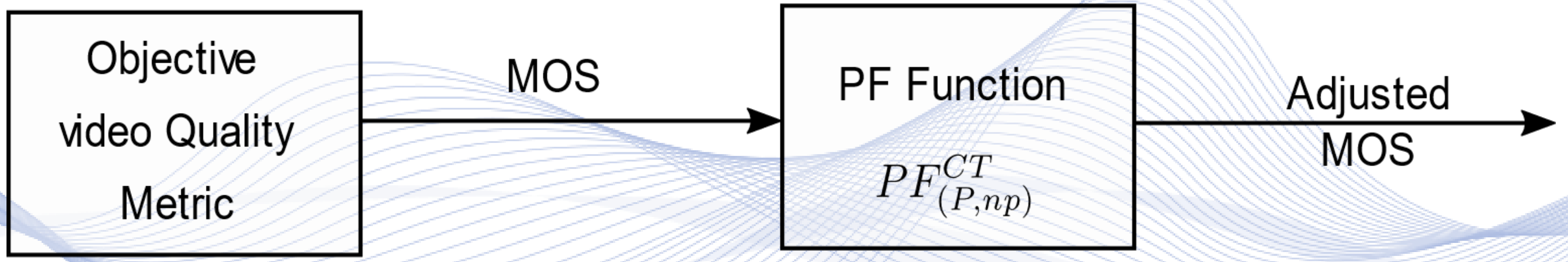

Fig.2 Preference factor function used to adjust a MOS index obtained by an objective video quality metric

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Objective Quality Assessment Methods

Based on the input data, the objective quality methods are separated into five categories [REN2014]:

- Parametric packet-layer models evaluate the MOS index only from the packet-header information without considering the media signals.
- Bitstream-layer models use encode bitstream and packet-layer information.
- Media-layer models compute the MOS index using the video signal.
- Parametric planning models require knowledge about the system being tested.
- Hybrid models are fusion of more than one of the models we already mentioned.

Objective Quality Assessment Methods

When it comes to the type of application service, objective quality methods are divided into two categories [REN2014] :

- In-service methods which have time restrictions because they are used in real time applications such as videoconference applications.
- Out-of-service methods which do not have time constrains, and are used in different tasks like video streaming services.

Objective Quality Assessment Metrics

- Objective quality metrics:
  - Psychophysical metrics
  - Engineering metrics
- The purpose of objective quality metrics is to automatically predict MOS with high accuracy.

Psychophysical Metrics

- They aim at modeling the HVS using aspects such as contrast and orientation sensitivity, frequency selectivity, spatial and temporal pattern, masking and color perception.
- They can be used for a wide variety of video degradations.
- Demanding computation.

Engineering Metrics

- Simplified metrics based on the extraction and analysis of certain features in a video [VQA2018].
- A set of features or quality – related parameters of a video are pooled together to establish an objective quality method, which can be mapped to predict MOS [VQA2018].

Engineering Methods

As in Image Quality Assessment, objective methods of Video Quality Assessment include full reference (FR), reduced reference (RR) and no – reference (NR) algorithms [VQA2018].

- FR methods: The entire original video is available to be compared with the distorted video.
- RR methods: Representative features of the characteristics of the original video are available.

Engineering Methods

- NR methods: They search for artifacts with respect to the pixel domain of a video, utilize information embedded in the bitstream of the related video format, or perform quality assessment as a hybrid of pixel – based and bitstream – based approaches.

Objective Quality Assessment Metrics

Video quality metrics are categorized in three more sections [ROV2012].

- **Requirements for reference video information** :

Video quality metrics of this section are categorized into three different kinds of metrics according to the amount of reference that someone has. Those metrics are, Full-Reference metrics, No-Reference metrics and Reduced-Reference metrics.

Full reference metrics: the observers has the entire video as a reference and by using the reference and the test video. Some metrics that belong to Full reference metrics are MSE, PSNR and HVS-based metrics.

Objective Quality Assessment Metrics

No reference metrics: the observer analyze only the test video and do not need any information about the reference video. They can be used in a compression and transmission system where the reference video is unavailable.

Reduced reference metrics: Reduced reference metrics extract a number of features from the reference video (e.g. the amount of motion or spatial details) and make a comparison between the reference and the test video based only on those features. They also are a fusion of full reference and no reference metrics.

Objective Quality Assessment Metrics

- **Analysis of the decoded video** :

  Video quality metrics are categorised into three kinds of metrics based on the way they analyze the decoded video.Those categories are the following: [ROV2012]

  - ***Data metrics:*** They measure the trueness of the video signal without considering anything from the HVS. Data metrics of this category are MSE and PSNR.
  - ***Picture metrics:*** They analyze the visual information contained in video data. According to the diferent ways of approaching a video design, picture metrics are classified into two categories: a vision modeling approach and an engineering approach.

Objective Quality Assessment Metrics

A vision modeling approach: accomplishes different ways to model the human vision aspects in order to predict with better results the evaluation of a video quality.

An engineering approach: deals with the extraction and analysis of certain features (e.g. structural elements such as contours) or artifacts in the video (such as blockiness and blur which are introduced by a particular compression technology).

- ***Packet- and bitstream-based metrics:*** It take into account the impact of network losses on video quality. Packet- and bitstreambased metrics extract some parameters from the transport stream and the bitstream with no or little decoding.

PEVQ metric

- Perceptual Evaluation of Video Quality
- Psychophysical metric
- Full reference metric
- It uses distortion classification of measures of the perceptual differences in the luminance and chrominance domains between corresponding frame [VQA2018].

Pixel – based Metrics

- The most used engineering metric [VQA2018].
- Peak Signal to Noise Ratio (PSNR): It is the proportion between the maximum signal and the corruption noise [PVQ]
- Video Structural Similarity Index (VSSIM)
    - SSIM values are calculated for all the frames but in the pooling stage the averaging is weighted based on motion between consecutive frames.

VMAF metric

- Video Multi – method Assessment Fusion (VMAF): It was recently proposed by Netflix as a full reference perceptual video quality assessment model that combines quality-aware features to predict perceptual quality. VMAF combines human vision modeling with machine learning, offering a good prediction of the video QoE. The VMAF score was computed using Netflix video streams delivered over TCP (i.e. without packet loss nor bit errors) to adjust compression and scaling parameters that ultimately impact QoE. [PVQ2019]
  - Engineering metric
  - Full reference metric
  - Used in Netflix

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Quality Assessment – Video Camera

The image or video quality can vary between different cameras, even if they have the same horizontal display resolution (2K, 4K etc.).

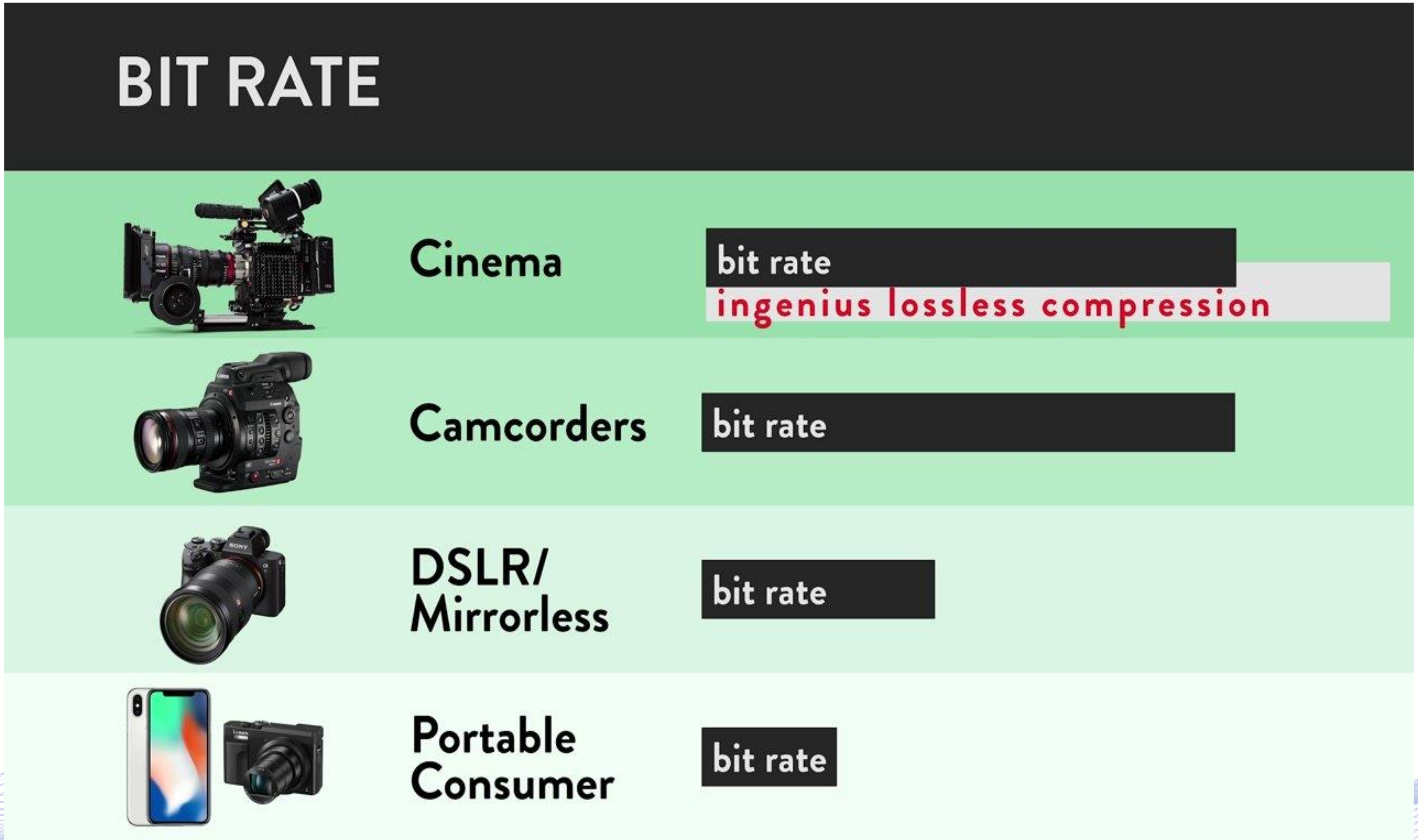
This is due to the main factors of a video camera and the way they affect the quality of the video [SPR2019].

There are three main factors:

- Bit Rate
- Bit Depth
- Chroma Subsampling

Bit Rate

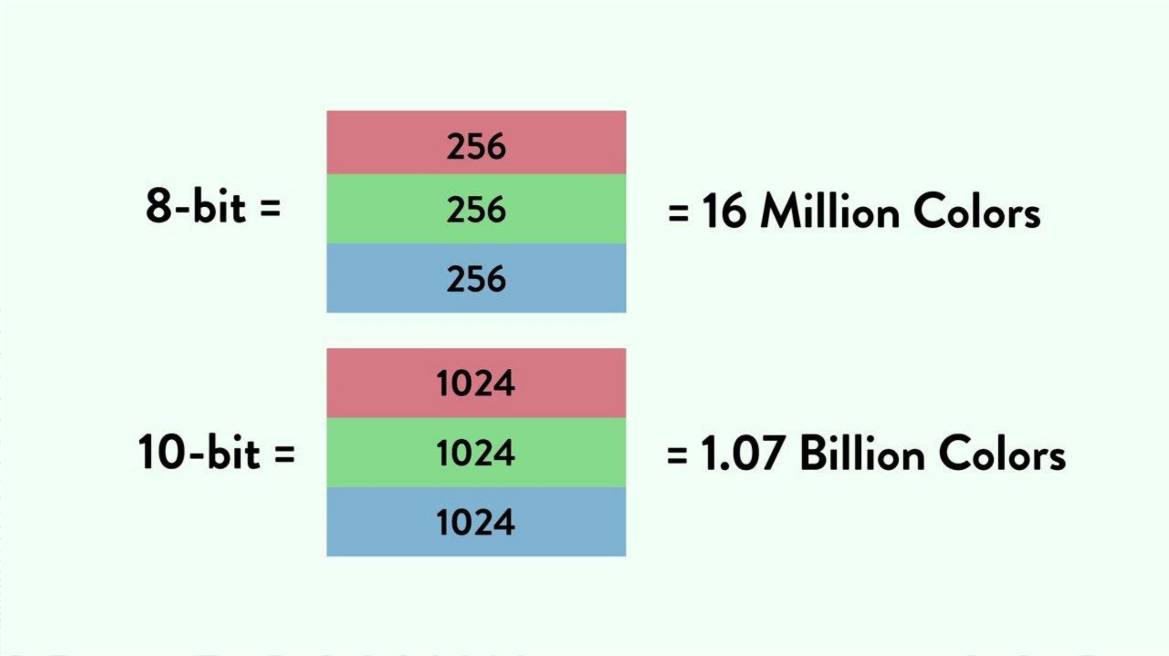
- The amount of data the camera records per second.
- A higher bit rate equates to higher quality footage.
  - It allows the camera to record more details about each frame.
- Once you hit the maximum bit rate the recording media can handle, bit rate levels off as a factor in image quality. Then, image compression becomes more important than bit rate for image quality [SPR2019].



Bit Rate of various devices [SPR2019].

Bit Depth

- The number of colors a camera can read per pixel [SPR].
- Common bit depths: 8-bit and 10-bit.
- The more colors are captured, the more processing power is required.



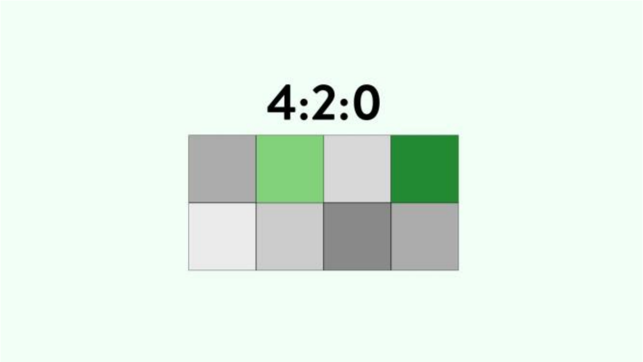
Bit Depth [SPR2019].

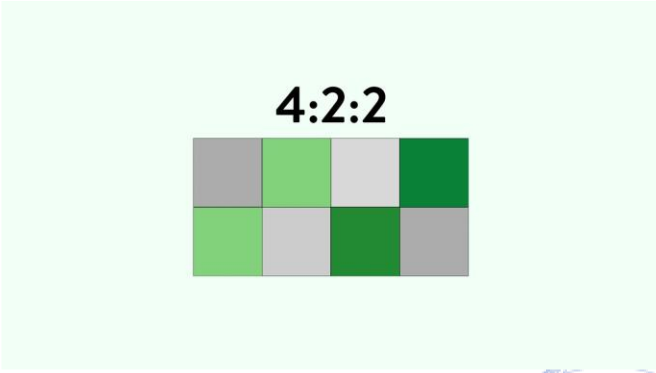
Chroma Subsampling

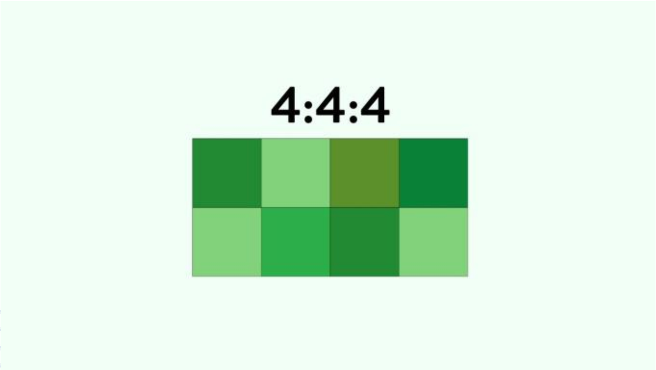
To save processing power, many cameras don’t capture color information about every single pixel. Instead, they fill in the gaps by “guessing” what’s in between [SPR2019].

- 4:2:0 chroma subsampling: For the first row of four pixels, the camera will capture information from two of them. For the second row, it won’t capture any.
- 4:2:2 chroma subsampling: The camera will capture color information from two pixels in each row of four.
- 4:4:4 chroma subsampling: The camera will capture information from every single pixel.

Chroma Subsampling







Chroma Subsampling [SPR2019].

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Q & A

Thank you very much for your attention!

More material in
http://icarus.csd.auth.gr/cvml-web-lecture-series/

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