Image Quality Summary

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Artificial Intelligence & Information Analysis Lab

Image Quality

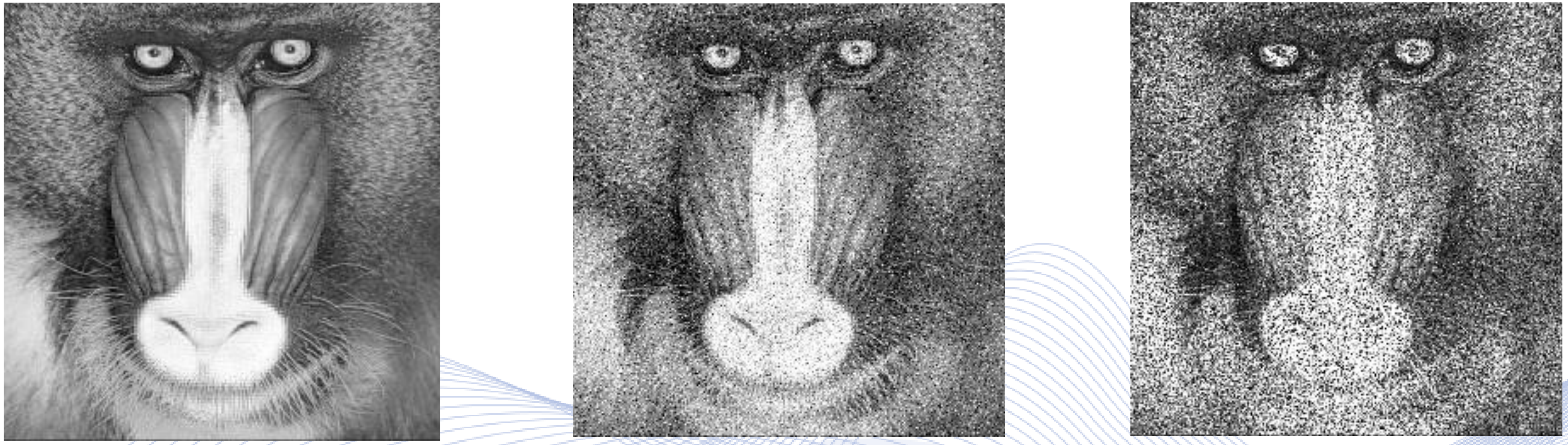
- **Introduction**
- Subjective Quality Assessment Methods
- Objective Quality Assessment
- Image quality metrics
- Full-reference Quality Assessment-Metrics
- Reduced-reference Quality Assessment
- No-reference Quality Assessment-Metrics
- Camera quality

Introduction

- Digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction,
- Any of them may result in a degradation of visual quality [WANG2004].
- In image communication systems, the communication channel tends to distort the image signal passing through it.
- The received image quality be monitored to meet requirements at the end receiver [BOVIK2005].

Introduction

(a) (b) (c)



Images of various qualities.

Introduction

Two classes of methods are used to evaluate image quality:

- Subjective Image Quality Assessment
- Objective Image Quality Assessment.

- ***Reference image***: Usually, an original image is used to be compared with the test/distorted image.

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Subjective Quality Assessment

Human judgment method

- The human vision is the determining factor for the image quality.
- This method is a trustworthy, but expensive and lengthy [PED2014].
- Subjective image quality experiments depend on various factors:
  - Viewing distance.
  - Display device characteristics (e.g., size),
  - Illumination intensity.
  - Viewer’s vision ability, mood and physical conditions.

Subjective Quality Assessment

Mean Opinion Score (MOS) measures subjective image quality.

- Observer ratings in the range $[1, \ldots, 5]$ are collected in a subjective quality evaluation test, involving N observers.
- Marks 1 or 5 correspond to the lowest/highest perceived image quality, respectively.
- It is the arithmetic mean over all individual observer scores $r_i, i = 1, \ldots N$:

$$MOS = \frac{1}{N}\sum_{0}^{N-1} r_i.$$

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Objective Quality Assessment

- In objective image quality assessment, we design mathematical models that can accurately the image quality, ***without using observers***.
- An objective image quality assessment method should be able to imitate the quality predictions of a human observer.

- The objective quality assessment methods are categorized into three families, depending on reference image availability [PED2014].

Objective Quality Assessment

- ***Full reference algorithms***: the reference image is entirely available to be compared with the distorted one.

- ***Reduced – reference algorithms***: we have only some, but not all the information about the reference image.
- ***No–reference algorithms***: only the distorted image is available, not the reference one.

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Image Quality Metrics

- The objective methods use objective image quality metrics in order to measure image distortion.
- Those metrics can be in the following categories [SIQ2009].

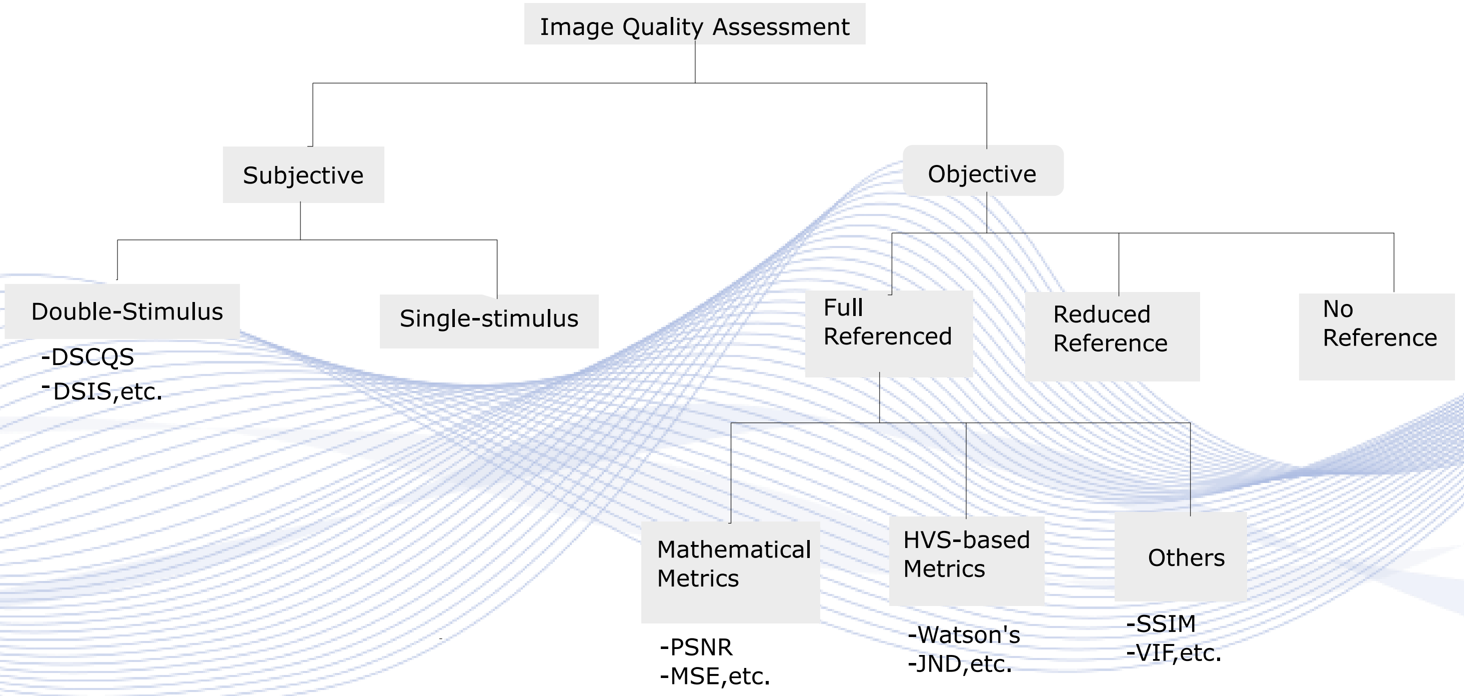

Fig. 1 : Image Quality Assessments

Image Quality Metrics

- ***Mathematical metrics:*** The image is considered as a signal, and the quality measure is calculated as the similarity (or difference) between the reference and the distorted images.
- ***HVS-based metrics:*** Here, the error signal, which is the difference between the reference and the test images, is normalized according to how much visible it is.
- ***Others:*** Here for example we have the structural similarity approach, where it is assumed that HVS (human visual system) is adapted to the natural scenes information which are pictures and videos of the visual environment. The structural similarity is formulated as mean of SSIM index. [SIQ2009]

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Full-Reference Quality Metrics

- ***Mean Squared Error*** (MSE) measures the average squared difference between actual and ideal pixel values [PED2014].
- ***Peak Signal to Noise Ratio*** (PSNR) indicates the ratio of the maximum pixel intensity to the power of the distortion.
- ***Structural Similarity Index Measure*** (SSIM) comprises three aspects of image similarity: luminance, contrast and structure. It agrees more with the subjective quality score [MW].
- ***Multiscale Structural Similarity Index Measure*** (MS-SSIM) takes into account multiple image scale information.

Full-Reference Quality Metrics

- ***Visual Information Fidelity*** (VIF) image quality metric is evaluated by defining and computing three components: source model, distortion model and HVS model.
  - It employs Gaussian Scale Mixture (GSM) probability models and natural image models in the wavelet domain.

- ***Most Apparent Distortion*** (MAD) is the average distance between each data value and the mean.

- ***Feature Similarity Index*** (FSIM) metric is evaluated by computing two components: image phase congruency) and image gradient magnitude and computing their similarity, when measured on the reference and test image, respectively [PED2014].

Mean Squared Error

Mean Square Error is computed in the image spatial domain as follows:

$$m = \frac{1}{N}\sum_{0}^{N-1}(x_i - y_i)^2.$$

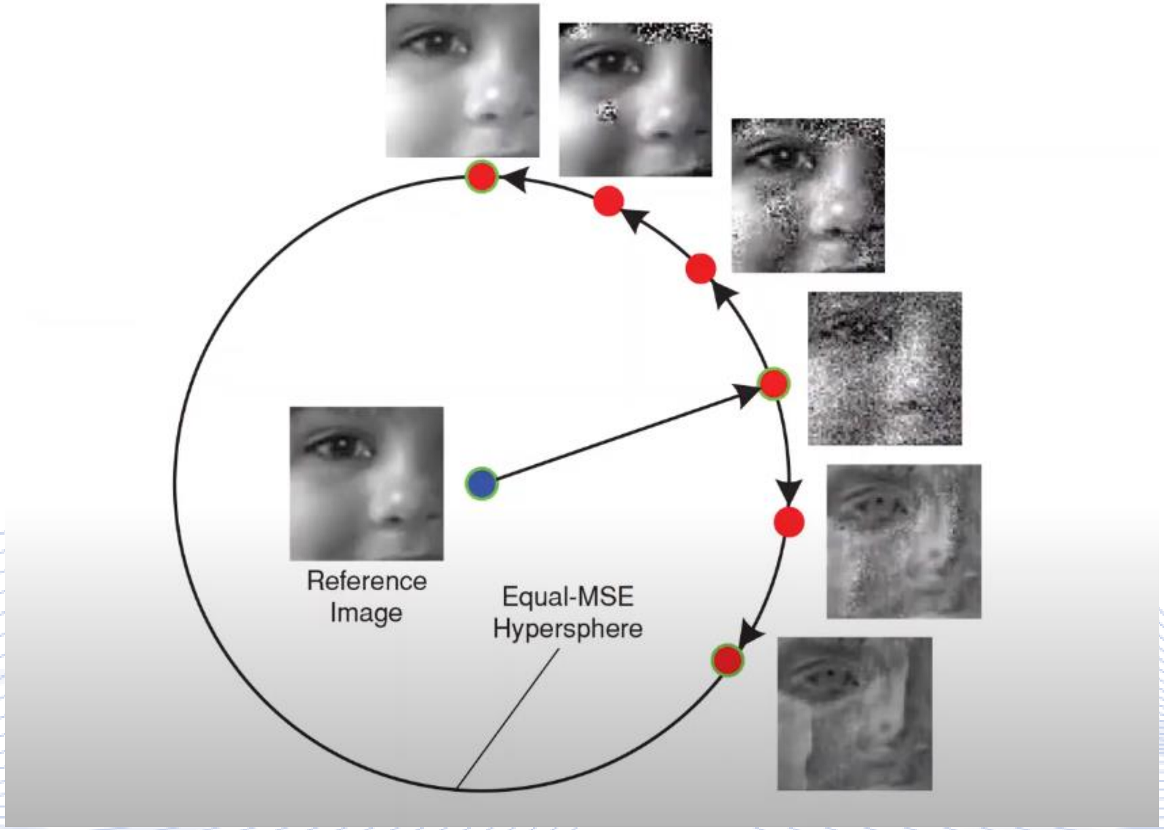
- N: number of pixels.
- x: reference image.
- y: test image.

Mean Squared Error

MSE has the following characteristics:

- It is a simple and computationally inexpensive method.
- It has a clear physical meaning physically.
  - It is the natural way of defining the intensity of an error signal.
- It is convex, symmetric and differentiable.
- It is extensively used for optimization and assessment in a wide range of signal processing applications [PED].

Mean Squared Error



Equal MSE hypersphere [WAN2009].

Peak Signal to Noise Radio

PSNR is given by:

$$p = 10\log_{10}\left(\frac{a_x^2}{m}\right) = 20\log_{10}\left(\frac{a_x}{\sqrt{m}}\right) =$$

$$= 20\log_{10}(a_x) - 10\log_{10}(m).$$

- a_x is the maximum possible pixel value of the image.
- m is the MSE between the reference and the test images.

Structural Similarity Index Measure

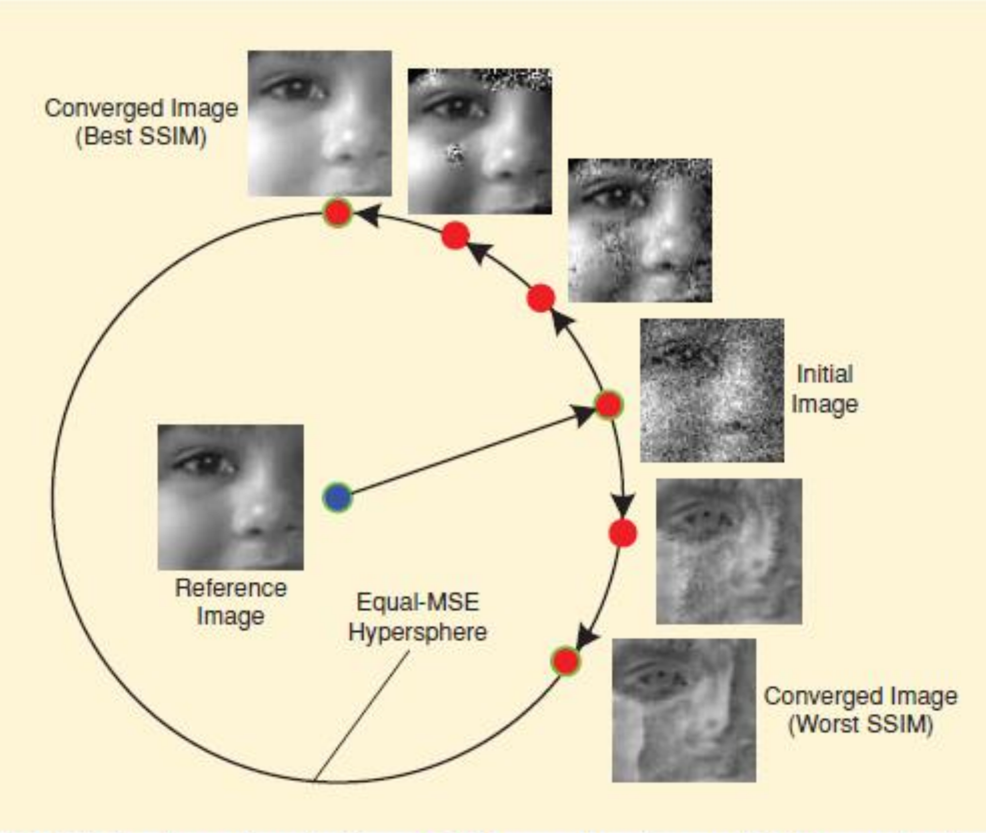


FIG4] Finding the maximum/minimum SSIM images along the equal-MSE hypersphere in mage space.

SSIM illustration [WAN2009].

Experimental results

Original

Salt and pepper noise

Compressed image

Contrast

Blurred image

Gaussian noise

Original image		
Sr. No.	Parameter of quality estimation	Value of quality
1	PSNR	∞
2	MSE	0
3	SSIM	1
Effect of Salt & pepper noise on image		
1	PSNR	32.9799
2	MSE	32.7404
3	SSIM	0.6783
Effect of Compression on image		
1	PSNR	33.3421
2	MSE	30.1209
3	SSIM	0.8146
Effect of Contrast on image		
1	PSNR	31.8423
2	MSE	42.5449
3	SSIM	0.4189
Effect of blurring on image		
1	PSNR	32.6303
2	MSE	35.4387
3	SSIM	0.6188
Effect of Gaussian noise on image		
1	PSNR	33.2935
2	MSE	30.4598
3	SSIM	0.8711

PSNR, MSE and SSIM for various image distortions [EST].

Experimental results

Figure 4 (a). Original image of Lena. (b). Salt & pepper noised image. (c). Compressed image. (d). Contrast image. (e). Blurred image. (f) Gaussian noise

Sr. No.	Parameter of quality estimation	Value of quality
Original image		
1	PSNR	∞
2	MSE	0
3	SSIM	1
Effect of Salt & pepper noise on image		
1	PSNR	31.9082
2	MSE	41.9044
3	SSIM	0.6249
Effect of Compression on image		
1	PSNR	32.9853
2	MSE	32.7003
3	SSIM	0.8053
Effect of Contrast on image		
1	PSNR	31.2264
2	MSE	49.0276
3	SSIM	0.5908
Effect of blurring on image		
1	PSNR	32.3714
2	MSE	37.6654
3	SSIM	0.7643
Effect of Gaussian noise on image		
1	PSNR	31.6018
2	MSE	44.9675
3	SSIM	0.6132

PSNR, MSE and SSIM for various image distortions [EST].

Multiscale SSIM

- ***Multiscale Structural Similarity Index*** (MS-SSIM)
- SSIM is a single-scale image quality measure.
- It reaches its peak performance, when is suitably adjusted.
- This SSIM disadvantage motivated the development of MS-SSIM. algorithm.

- In MS-SSIM and other multi-scale image quality measures, multi-scale method image features at various resolutions and viewing conditions influence image quality assessment [PED2014].

Visual Information Fidelity

Source model.

- ***Visual Information Fidelity*** (VIF) models natural image quality in wavelet domain using ***Gaussian Scale Mixture*** (GSM) models.
- A GSM of a reference image c is a random field, which is an element-wise product of two random fields [PED2014]:

$$c = \mathbf{Z} \otimes \mathbf{u}.$$

- $\mathbf{Z}$: random field containing positive scalars.
- $\mathbf{u}$: zero-mean Gaussian random vector.

Visual Information Fidelity

Wavelet image transform [2DWAV] .

Most Apparent Distortion

Most Apparent Distortion (MAD) algorithm presumes that the HVS employs two different tactics when evaluating the image quality:

- detection-based tactic and
- appearance-based tactic.

Detection-based tactic.

- The HVS goes through the image, searching for distortions.
- Since image content can influence distortion recognition, a spatial domain measure of contrast masking is used.

Most Apparent Distortion

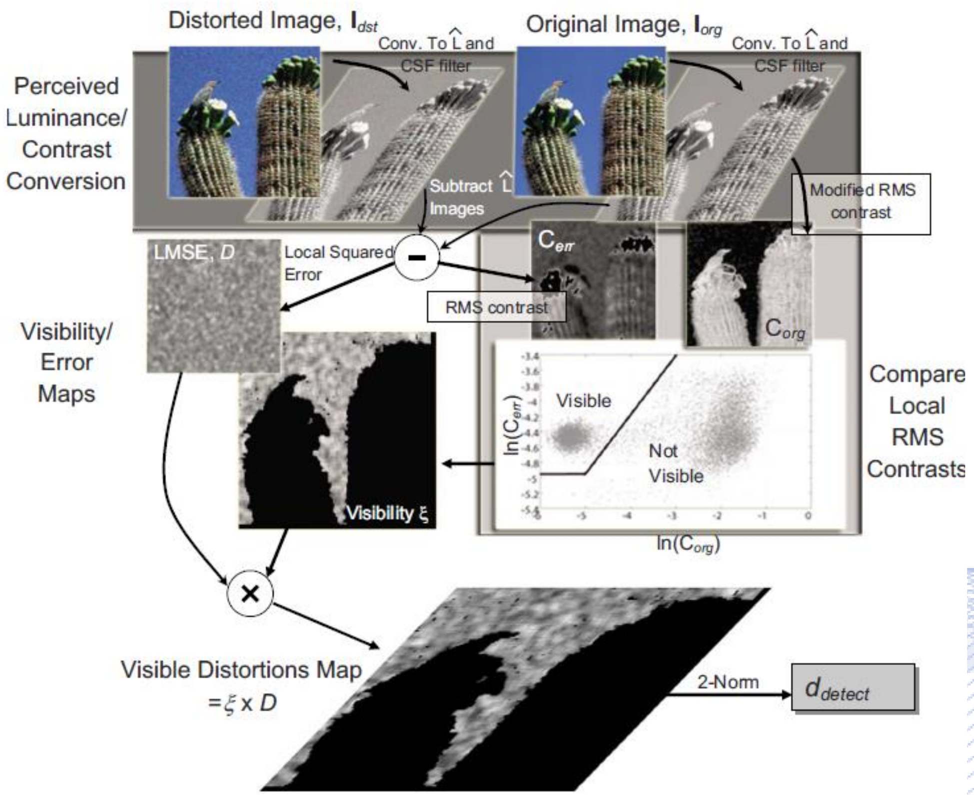


Fig. 3 Evolution of original and distorted image Cactus during the calculation of d_{detect}. Also shown is

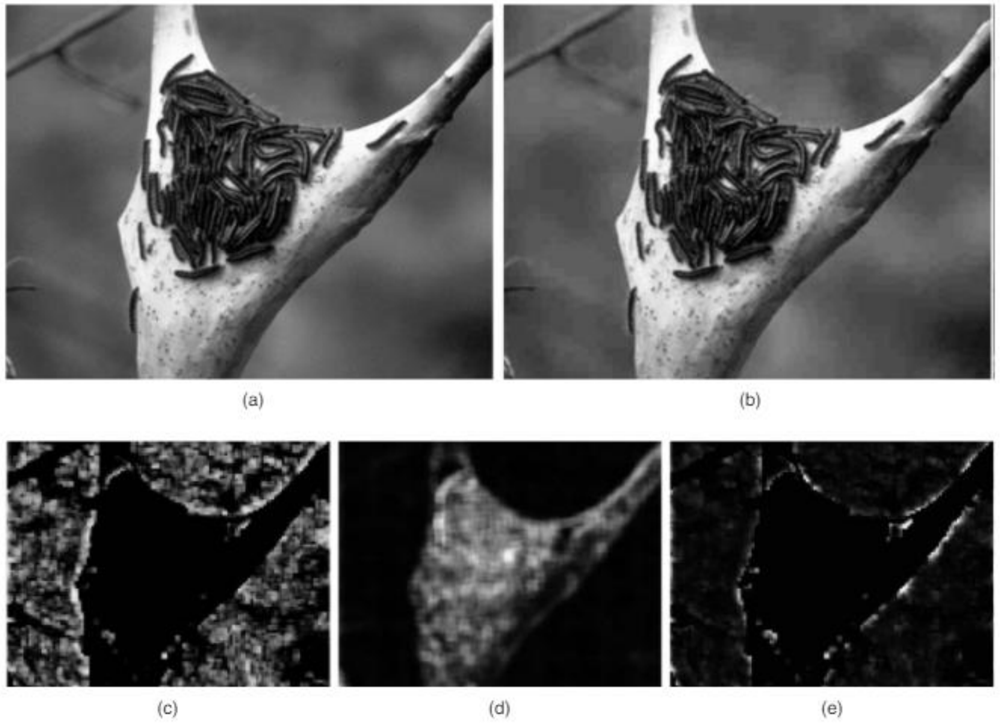


Fig. 4 Perceived distortion in the high-quality regime is determined based largely on masking. Given an original image (a), and a distorted image (b), a map denoting the locations of visible distortions is computed (c), which is then multiplied by local MSE measured in the lightness domain (d). The resulting visibility-weighted local MSE (e) is used to determine d_{detect}. In this image, the only visible distortions occur in the form of blocking in the background and ringing around the branches, whereas the worms and the interior of the tree mask these errors. Because local MSE does not take into account masking, the local MSE map in (d) indicates that the greatest distortions occur in the areas of greatest energy. However, by augmenting local MSE with the distortion visibility map, the final visibility-weighted local MSE map (e) accurately reflects the locations and amounts of visible distortions.

Detection distortion d_c[MD2010].

Most Apparent Distortion

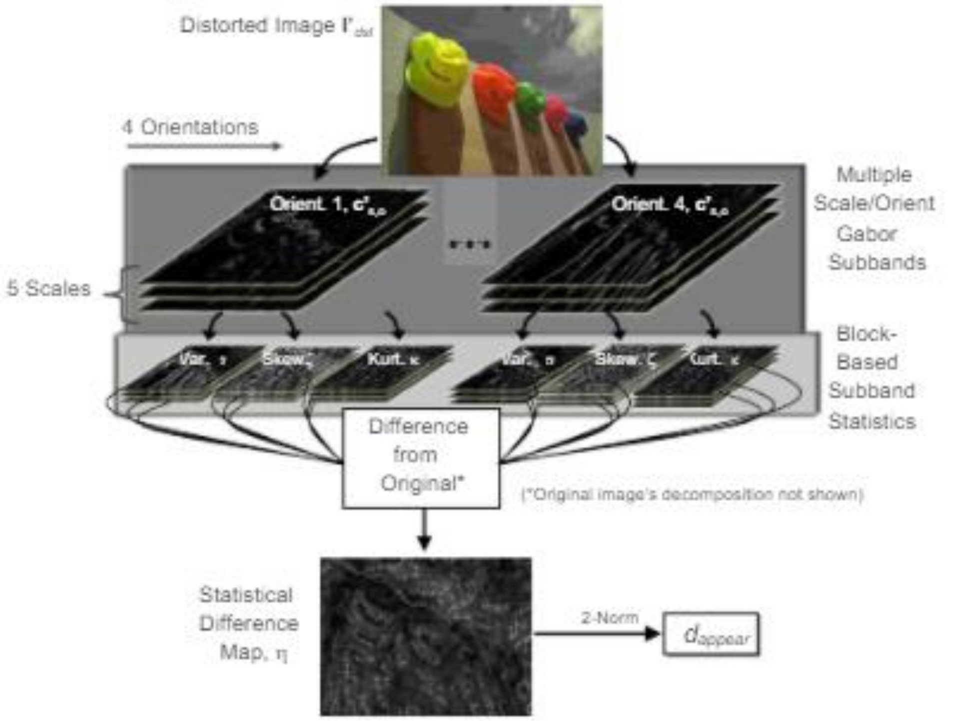


Fig. 5 Evolution of distorted image Caps during the calculation of d_{appear}. The decomposition of the original image is not shown but follows an identical process.

Fig. 6 Perceived distortion in the low-quality regime is determined based largely on changes in the appearance of the image's subject matter. Given an original image (a), and a distorted image (b), a map of local changes in log-Gabor filter-response statistics is computed (c). This statistical difference map is used to determine d_{appear}. Note that the difference map is based on statistics from multiple scales, so distortions are not completely localized.

Appearence distortion [MD2010].

Feature Similarity Index

Feature Similarity Index (FSIM).

FSIM algorithm uses two kinds of image quality properties:

- ***Phase congruency*** (PC) is used as the primary FSIM property.
  - Phase congruency is a measure of ***feature significance*** in computer images.
  - However, PC is contrast-invariant.

- The ***image gradient magnitude*** (GM) is used as the secondary FSIM characteristic as our perception of an image quality is influenced by local contrast of that image [PED2014] .
  - It is calculated by finding the local image edge detection and magnitude.

Feature Similarity Index

(a) (b) (c) (d) (e) (f)

Fig. 4: (a) A reference image; (b) ~ (f) are the distorted versions of (a) in the TID2008 database. Distortion types of (b) ~ (f) are "*additive Gaussian noise*", "*spatially correlated noise*", "*image denoising*", "*JPEG 2000 compression*", and "*JPEG transformation errors*", respectively.

FSIM calculation [FS2011].

Feature Similarity Index

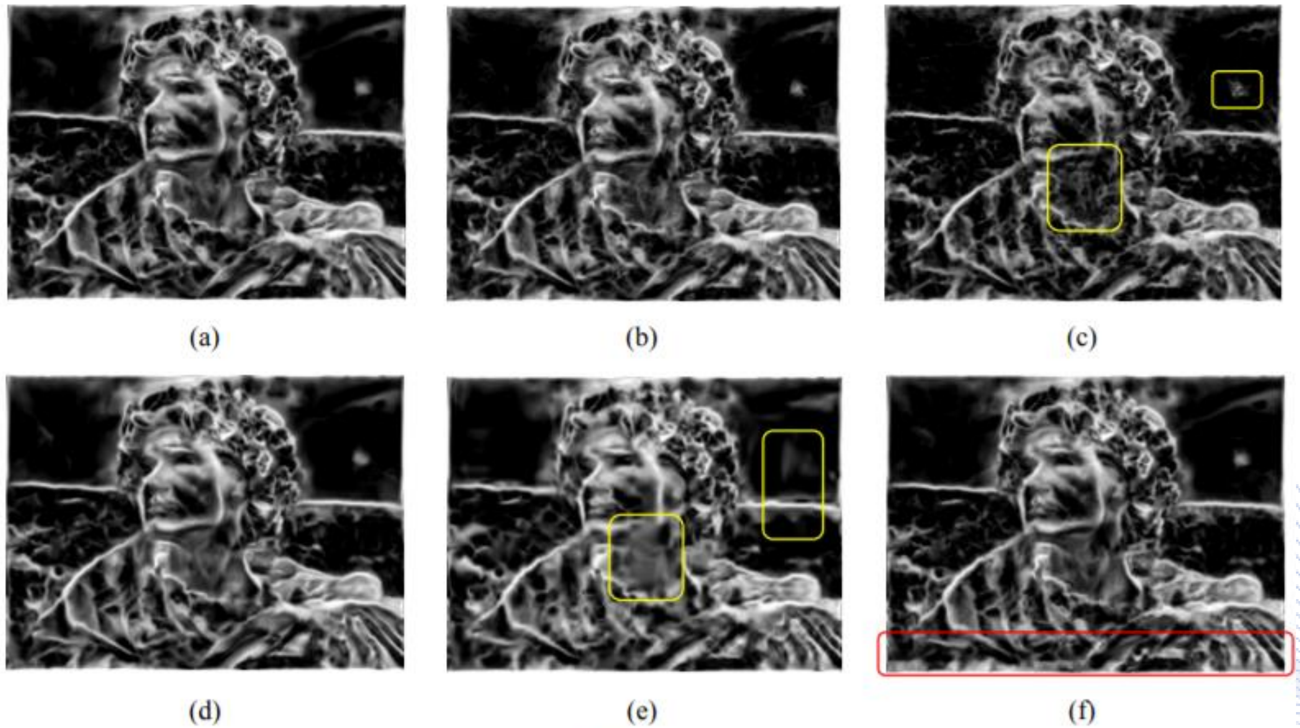


Fig. 5: (a) ~ (f) are PC maps extracted from images Figs. 4a ~ 4f, respectively. (a) is the PC map of the reference image while (b) ~ (f) are the PC maps of the distorted images. (b) and (d) are more similar to (a) than (c), (e), and (f). In (c), (e), and (f), regions with obvious differences to the corresponding regions in (a) are marked by colorful rectangles.

FSIM calculation [FS2011].

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Reduced-Reference Image Quality Assessment

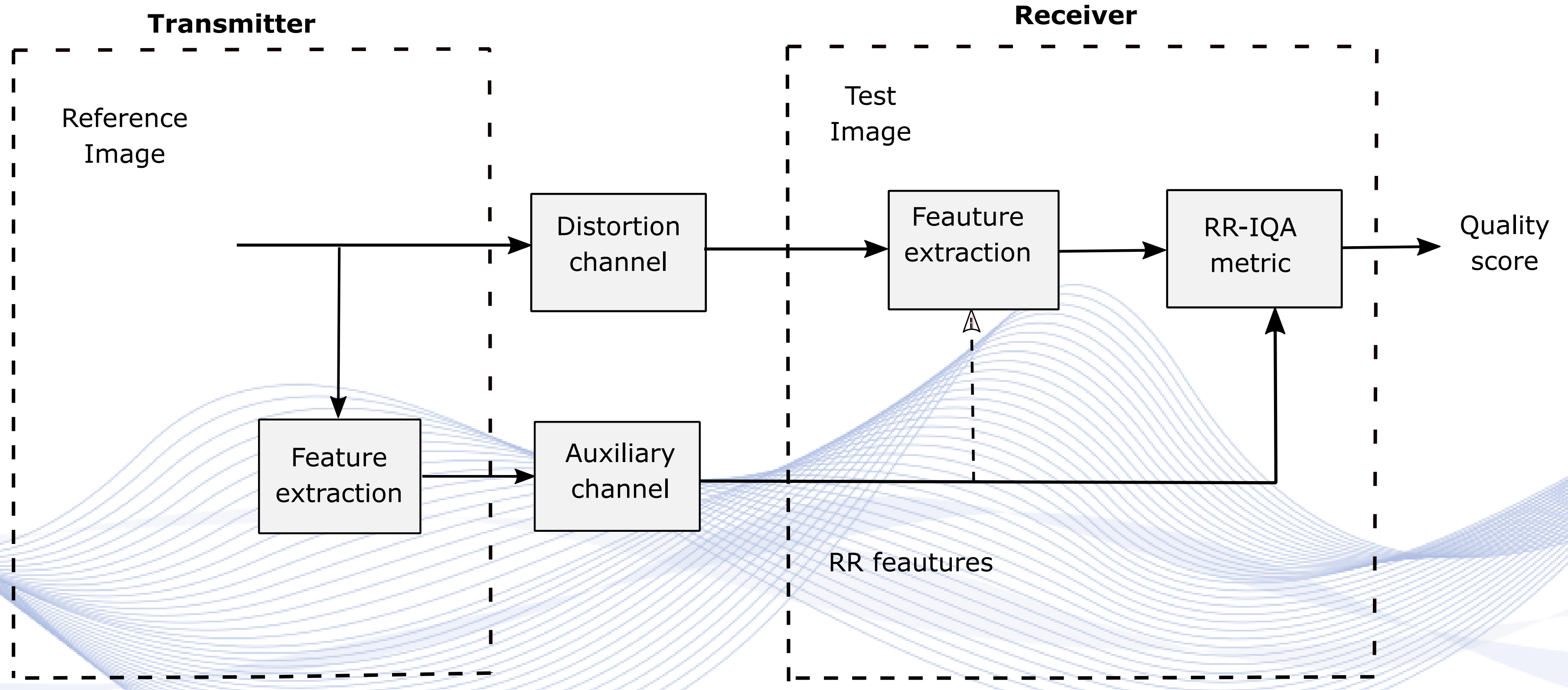

Fig.1 The framework of an RR-IQA system.

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Reduced-Reference Image Quality Assessment

Reduced-Reference Image Quality Assessment (RRIQ-A).

- Feature extraction is performed on the reference image at the transmitter site [PED2014].
- The image features are transmitted to the image through an ancillary channel.
- The same process is also applied to the test image at the receiver.
- Feature extraction is performed on the received (distorted) image at the receiver [PED2014].

- The features of both the reference and received image are compared to assess received image quality.

Reduced-Reference Image Quality Assessment

RR-IQA method categories [PED2014] :

- ***Methods based on the image source models.*** They are statistical models that capture a priori low-level statistical properties of natural images.
  - They have low data rate, as they can summarize the image information efficiently.
- ***Methods based on capturing image distortion information.*** They are most useful when sufficient image distortion information is available.
  - They can only work for known distortions used in their design.
- ***Methods based on HVS models.*** They employ results from physiological and psychophysical HVS studies.

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No-Reference Image Quality Assessment

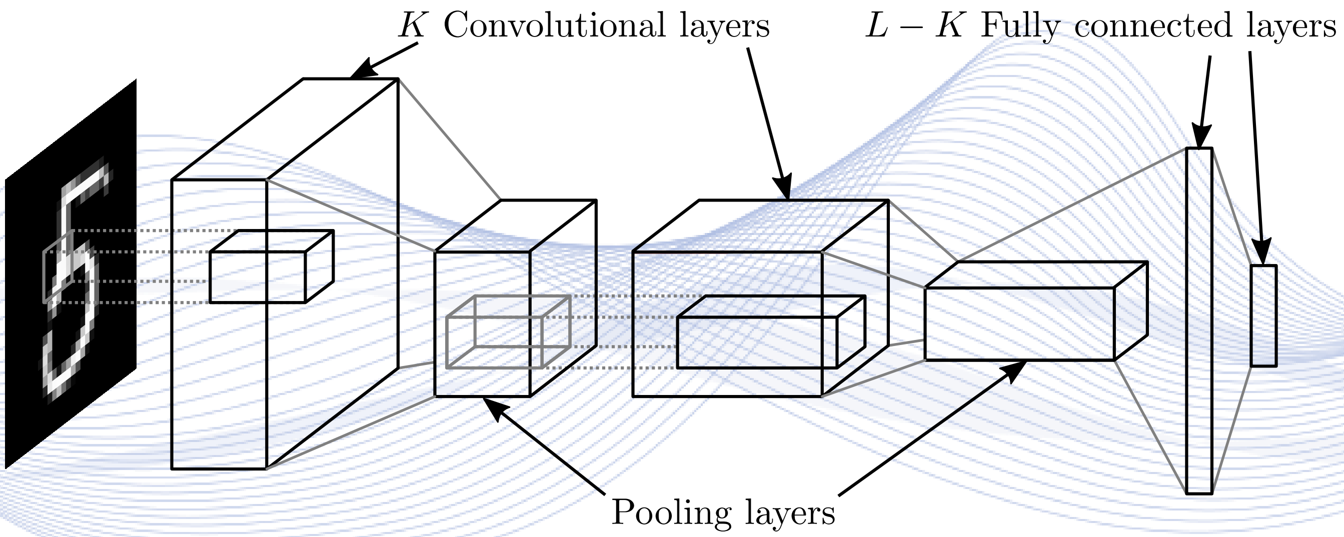
Convolutional Neural Networks (CNN) have been used for no reference image quality assessment [DAV2014].

- For a standard gray scale image, a local luminance normalization is performed, followed by non-overlapping image patch sampling.
- A trained CNN is used to evaluate the quality score for each test image patch.
- The average patch score provides a quality estimation for the test image.

No-Reference Image Quality Assessment

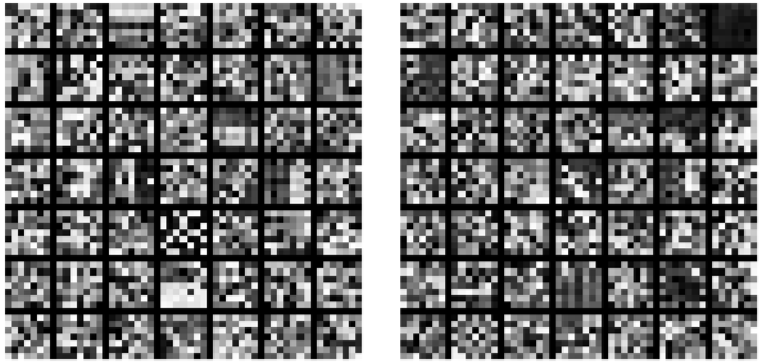
Convolutional Neural Networks (***CNN***):

- employ image convolutions in the first layers.
- They may employ fully connected MLPs in the last layers.



Basic CNN structure.

No-Reference Image Quality Assessment



(a) (b)

Figure 2: Learned convolution kernels on (a) JPEG (b) ALL on LIVE dataset

Figure 6: Local quality estimation results on examples of non-global distortion from TID2008. Column 1,3,5 show (a) jpeg transmission errors (b) jpeg2000 transmission errors (c) local blockwise distortion. Column 2,4,6 show the local quality estimation results, where brighter pixels indicate lower quality.

Example of No-Reference Image Quality Assessment [DAV2014].

No-Reference Image Quality Assessment

- ***Blind/Referenceless Image Spatial Quality Evaluator*** (BRISQUE).
  - It is trained on a database of images with known distortions.
  - It is limited to working only on the same type of distortion [MW].
- ***Natural Image Quality Evaluator*** (NIQE). Although it is trained on a database of undistoreted images, it can measure the quality of images with arbitrary distortion.
- ***Perception based Image Quality Evaluator*** (PIQE). It can measure the quality of images with arbitrary distortion.

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Camera Quality

- ***Illumination quality*** is equally important to camera quality, but still does not guarantee the acquired image quality [VCF2014].

- ***Lens aperture*** is its maximum opening.
  - The bigger the aperture, the more light is gathered, and the less light is needed for a good photo.
- ***Lens focal length.***
  - A zoom lens has a variable focal length.
  - Short focal length (wide-angle lens), is great for taking long shots.
  - A long focal length (telephoto lens), allowing you to get a tight photo of a distant object or person.

Camera Quality

- ***Lens quality.***
  - A poor lens slightly blurs images.
  - It may exhibit chromatic aberration, which produces colored fringes at high contrast edges.
- ***Image sensor size and number of image pixels*.**
  - The larger the sensor is, the better the image quality.
  - Sensor size affects pixel size and the number of image pixels.
- ***Image sensor sensitivity.***
  - In low light conditions images can be noisy.
  - Sor same sensor size, sensor sensitivity is inversely proportional to the number of image pixels.

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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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