New Directions in Image and Video Quality Assessment

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Prologue

I seek analogies between assessment of visual signal quality

and

measuring the fidelity of a communication system

in hopes

that the powerful tools of that mathematical discipline may be brought to bear





A Classic Communication System



- Source
- Encoder
- Encrypter
- Modulator

- Noise
- Interference
- Distortion
- Fading

- Decoder
- Decrypter
- Demodulator
- Interface





Basic Tenet of Communication Theory

- The more known about
 - the transmitter
 - the channel
 - the reciever

the better job of **communication** can be done

• Provided the models of transmitter, channel and receiver are accurate.





Image Quality Assessment

What are the transmitter, channel, and receiver....?





The Natural Image Transmitter











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Photos of the natural image transmitter



Natural Image Transmitter

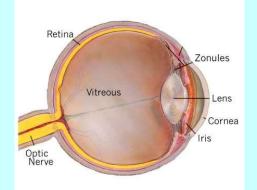
- Also called "the real world."
- Produces Natural Image Signals light fields emitted/reflected from objects.
- *Natural Scene Statistics* (NSS) are still being learned.
 These models are in a nascent stage.

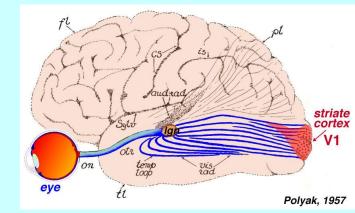




The Natural Image Receiver







Depictions of the natural image receiver









The Natural Image Receiver

- Also called the *Human Visual System* (HVS).
- Sophisticated models for: optics, retinal neurons, postretinal neurons, cortical receptive fields, gain control, masking, threshold visibility etc.
- Yet we have only begun to penetrate the exquisite sophistication of the HVS. Our receiver model is very incomplete.





Overall Communication System

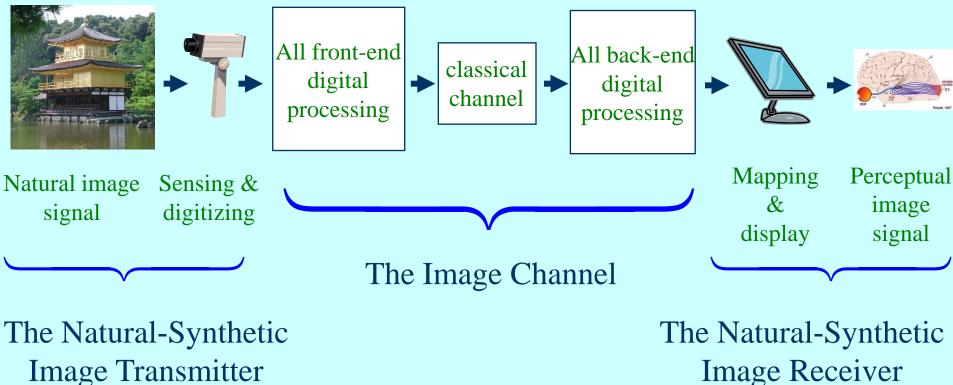
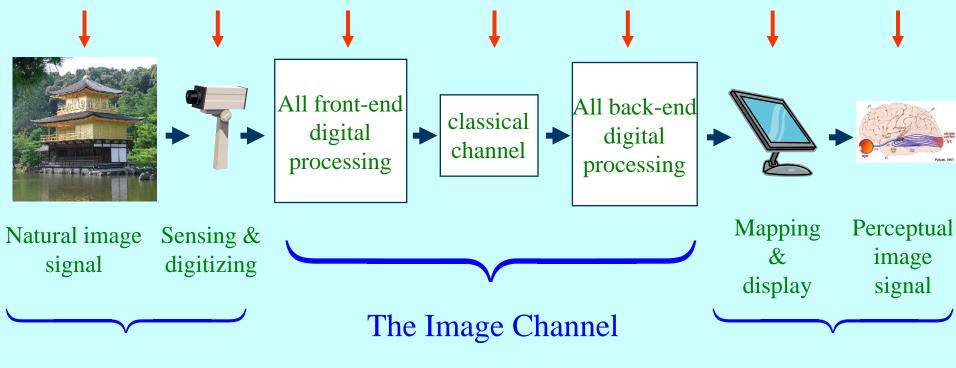




Image Receiver



Sources of Image Distortion



The Natural-Synthetic Image Transmitter



The Natural-Synthetic Image Receiver



Four Classes of QA Algorithm

"Full-Reference" QA

"No-Reference" or Blind QA

"Reduced-Reference" QA

"Distortion-Specific" QA





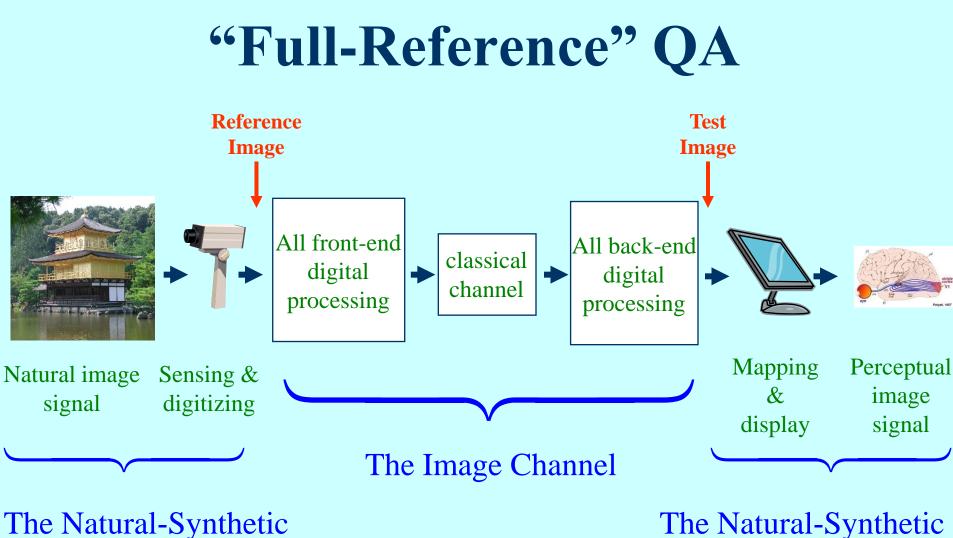


Image Transmitter



The Natural-Synthetic Image Receiver



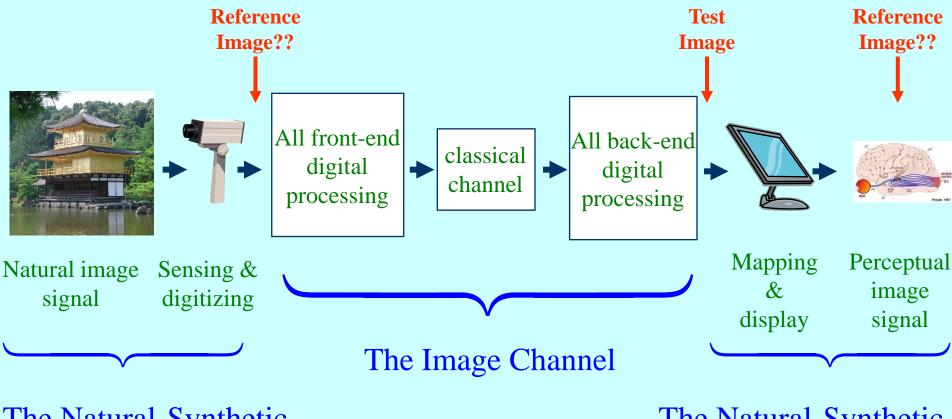
"Full-Reference" QA

- Depends on accurate statistical models of the transmitter: How far does the test image depart from "normal behavior"?
- Depends on accurate statistical models of the receiver: How far does the test image depart from "normal appearance"?
- Must be baselined against human subjectivity large, statistically significant human studies.





"No-Reference" or Blind QA



The Natural-Synthetic Image Transmitter



The Natural-Synthetic Image Receiver



Perhaps it depends on whether the viewer is an ornithologist...

.... or a botanist....

his a "good quality" image?

Blind QA

- Will require profound insights into natural image modeling and image appearance modeling.
- I do not include "Blind QA with known distortion type"





"Reduced-Reference" QA

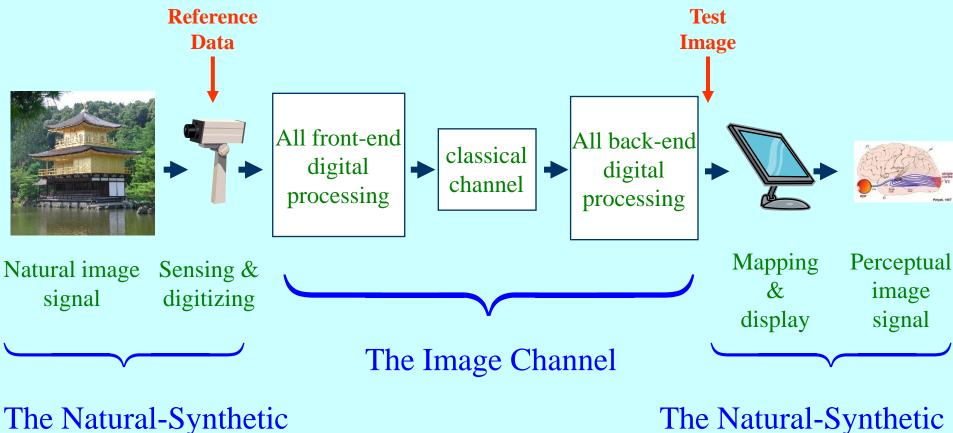


Image Transmitter



The Natural-Synthetic Image Receiver



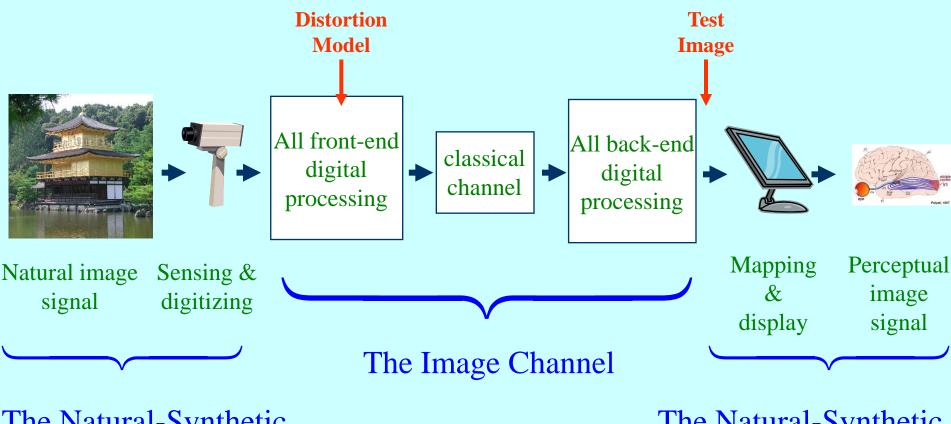
"Reduced-Reference" QA

- No reference image, but **side information** sent with the transmitted image.
- Side info: Partial wavelet data; edge locations; local statistics, etc. Promising but requires application- & domain-dependent assumptions.
- Not discussed here.





"Distortion-Specific" QA



The Natural-Synthetic Image Transmitter



The Natural-Synthetic Image Receiver



"Distortion-Specific" QA

- Blind, reduced reference, **or** full reference.
- Channel distortion(s) known, e.g. JPEG blocking. Effective for specific applications.
- Not generic; not covered here.



Predictable distortion artifacts?





Summary to This Point

- I've attempted to begin casting image & video QA as a problem in classical communications theory.
- Much work to be done in accurately modeling transmitter, receiver and channel.
- As these **models improve**, I believe we will rely on principles of mathematical communication theory to **significantly improve** modern QA algorithms.





IQA Algorithms

And now some discussion of existing IQA algorithms, old and new ...





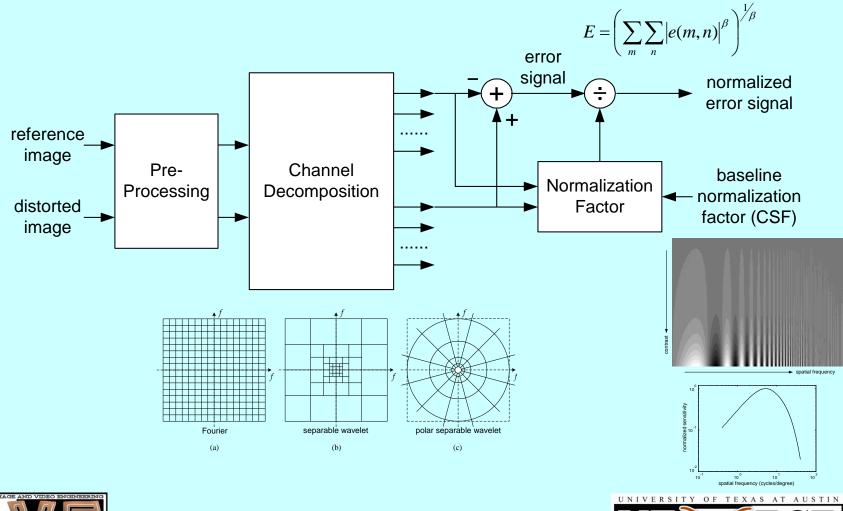
Receiver-Oriented Algorithms (FR)

- Older approaches based on models of human visual function and on measured perception.
- Largely limited to front-end models of the visual pathway. Idea: emulate the visual pathway.
- Lubin, Daley, Watson, JNDMetrix, PQS, all generally complex/expensive.
- No longer generally competitive for still images.





Receiver-Oriented Algorithms



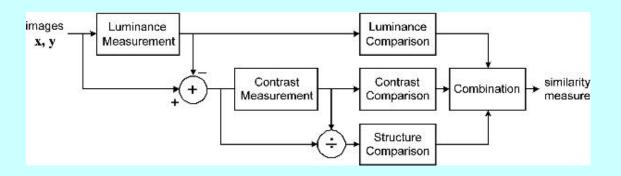


(Eventually) will again be the basis for the best QA algorithms (IMHO)



Structural Similarity (SSIM) Index

• Popular algorithm that uses weighted local (patch) image statistics:



$SSIM_{\mathbf{I},\mathbf{J}}\left(i,j\right) = L_{\mathbf{I},\mathbf{J}}\left(i,j\right) \cdot C_{\mathbf{I},\mathbf{J}}\left(i,j\right) \cdot S_{\mathbf{I},\mathbf{J}}\left(i,j\right)$

local luminance similarity

local structural similarity

local contrast similarity



Wang & Bovik, *IEEE Signal Processing Letters*, March 02 Wang, Bovik, Sheikh & Simoncelli, *Trans on IP*, March 04



Structural Similarity (SSIM) Index

• Pointwise SSIM Index or SSIM Map:

$$\text{SSIM}_{\mathbf{I},\mathbf{J}} = \left(\frac{2\mu_{\mathbf{I}}\mu_{\mathbf{J}} + C_1}{\mu_{\mathbf{I}}^2 + \mu_{\mathbf{J}}^2 + C_1}\right) \cdot \left(\frac{2\sigma_{\mathbf{I}}\sigma_{\mathbf{J}} + C_2}{\sigma_{\mathbf{I}}^2 + \sigma_{\mathbf{J}}^2 + C_2}\right) \cdot \left(\frac{2\sigma_{\mathbf{I}\mathbf{J}} + C_3}{\sigma_{\mathbf{I}}\sigma_{\mathbf{J}} + C_3}\right)$$

local luminance similarity

local contrast similarity

local structural similarity

• Mean SSIM Index

$$SSIM(\mathbf{I}, \mathbf{J}) = \left(\frac{1}{NM}\right) \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} SSIM_{\mathbf{I}, \mathbf{J}}(i, j)$$

 Multiscale SSIM (MS-SSIM) operates over a dyadic pyramid (best SSIM performance) Wang, Simoncelli & Bovik, Asilomar, Nov 2003





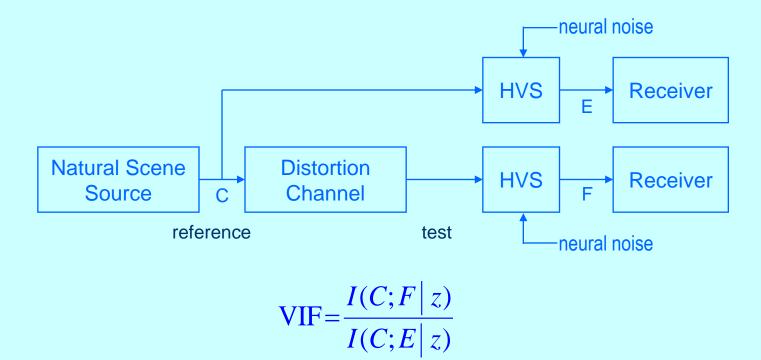
Comments on SSIM

- A distortion-blind full-reference method.
- Heuristic/Intuitive! Not derived from any specific image formation or perceptual models.
- Transmitter-Near-Optimal? Images are well described by local luminances (smooth patches), variances (textures), and structures (edges and details).
- *Receiver-Near-Optimal?* Perceptual quality depends on faithful rendering of local luminance, variation, and structure. And that quality perception of these is *separable*.





Visual Information Fidelity Index



I(*C*; *F*/*z*) is mutual information in the wavelet domain conditioned on scalar variance field *z* (estimated)



Sheikh, Bovik & DeVeciana, *Trans on IP*, Dec 05 Sheikh & Bovik, *Trans on IP*, Feb 06



VIF Index

- Distortion-Blind Full Reference IQA algorithm.
- Numerator measures the information that the HVS can extract *from the distorted image*.
- Divisive normalization by the information that the HVS can extract *from the reference*.
- Simple models used: statistical transmitter model (GSM) channel model (blur + noise) simple wavelet + neural noise receiver model.





GSM Model – Statistical Transmitter Model

• **Image wavelet coefficients** modeled as Gaussian-scale mixture:

$$\boldsymbol{X} \sim \boldsymbol{z}\boldsymbol{U}$$

where z = space-varying variance field, and U are standard normal.

- Independent Gaussian when conditioned on variance.
- Simple, effective transmitter model.





Relative Performance

- The LIVE Image Quality Assessment Database over 25,000 subjective judgements Mean Opinion Scores (MOS). Recent Release 2 includes Differential MOS (DMOS) values as well.
- Widely used and cited over 200 institutions have downloaded the (>1GB) LIVE database.

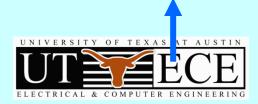
| | JP2K#1 | JP2K#2 | JPEG#1 | JPEG#2 | WN | GBlur | FF | All data |
|-----------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| PSNR | 0.9263 | 0.8549 | 0.8779 | 0.7708 | 0.9854 <mark>1</mark> | 0.7823 | 0.8907 | 0.8755 |
| JND | 0.9646 <mark>2</mark> | 0.9608 | 0.9599 | 0.9150 | 0.9487 | 0.9389 | 0.9045 | 0.9291 |
| DCTune | 0.8335 | 0.7209 | 0.8702 | 0.8200 | 0.9324 | 0.6721 | 0.7675 | 0.8032 |
| PQS | 0.9372 | 0.9147 | 0.9387 | 0.8987 | 0.9535 | 0.9291 | 0.9388 | 0.9304 |
| NQM | 0.9465 | 0.9393 | 0.9360 | 0.8988 | 0.9854 <mark>1</mark> | 0.8467 | 0.8171 | 0.9049 |
| Fuzzy S7 | 0.9316 | 0.9000 | 0.9077 | 0.8012 | 0.9199 | 0.6056 | 0.9074 | 0.8291 |
| BSDM (S4) | 0.9130 | 0.9378 | 0.9128 | 0.9231 | 0.9327 | 0.9600 | 0.9372 | 0.9271 |
| SSIM(MS) | 0.9645 <mark>2</mark> | 0.9648 <mark>2</mark> | 0.9702 <u>1</u> | 0.9454 <mark>1</mark> | 0.9805 | 0.9519 | 0.9395 | 0.9527 <mark>2</mark> |
| IFC | 0.9386 | 0.9534 | 0.9107 | 0.9005 | 0.9625 | 0.9637 <mark>2</mark> | 0.9556 <mark>2</mark> | 0.9459 |
| VIF | 0.9721 <mark>1</mark> | 0.9719 <mark>1</mark> | 0.9699 <mark>2</mark> | 0.9439 <mark>2</mark> | 0.9828 <mark>2</mark> | 0.9706 <mark>1</mark> | 0.9649 <mark>1</mark> | 0.9584 <mark>1</mark> |

Spearman Rank-Order Coefficient

LABORATORY FOR IMAGE AND VIDEO ENGINEERING THE UNIVERSITY OF TEXAS AT AUSTIN

Sheikh, Sabir & Bovik, Trans on IP, Nov 06

Note: IFC is VIF w/o divisive normalization



THE MSE

 For 40 years the Mean-Squared Error has dominated signal quality assessment

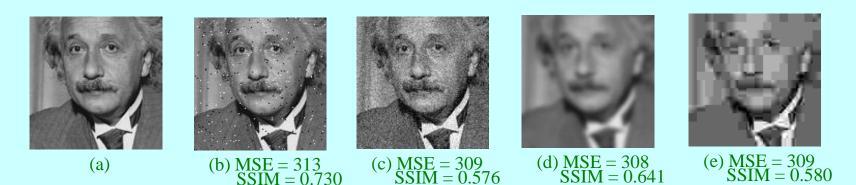
• As well as design and optimization





DUMP THE MSE!

 The MSE and hence PSNR are (generally) awful measures of image quality.

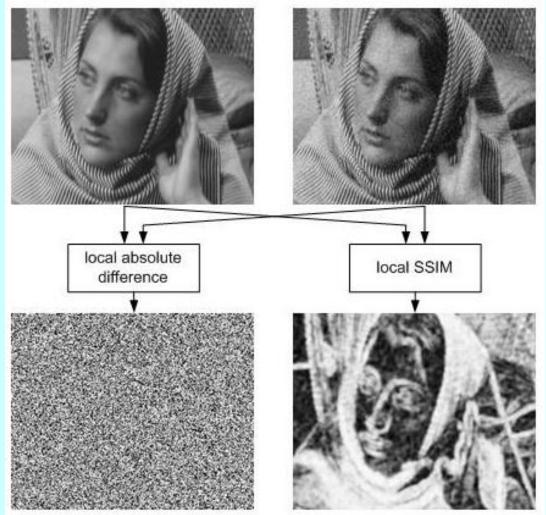


Einstein altered by different distortions. (a) reference image; (b) impulse noise; (c) Gaussian noise; (d) blur; (e) JPEG compression.





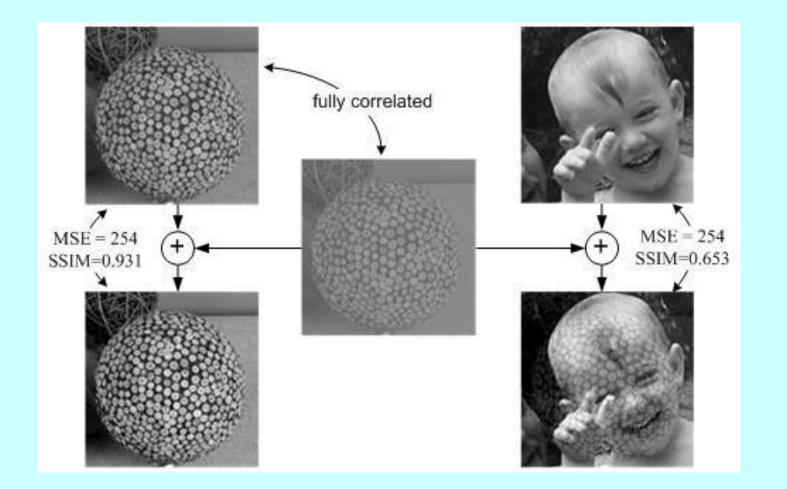
DUMP THE MSE!!







DUMP THE MSE!!!







Towards Video Quality Assessment

- *Frame-by-frame* SSIM and VIF produces competitive results relative to sophisticated receiver-based algorithms.
- Video distortions are very different from pure spatial distortions and require **spatio-temporal measurements**.
- **Temporal masking** effects play an important role in the perception of spatial distortions.
- Evaluation of VQA algorithms no mean task (more later)





Video Distortions

 Spatio-temporal artifacts include ghosting, motion blocking, motion compensation mismatches, mosquito effect, jerkiness, smearing, and more.

 Quality Assessment of videos distorted by such processes must rely on effective handling of motion.





Motion and Optical Flow

- Simple method Differential-VIF (Sheikh-Bovik '05)
- VIF operating in the wavelet *derivative* domain. Improved performance relative to frame-by-frame.
- Current (developing) approach: model optical flow and measure video quality along the motion trajectories





Performance

Spearman Rank Order Correlation Coefficient (SROCC) between subjective and objective scores for different quality metrics. *Proponent P8 is the best performing metric tested by the VQEG in terms of SROCC

| Quality Model | SROCC |
|--------------------------------|-------|
| PSNR | 0.786 |
| Proponent P8 (Swisscom)* | 0.803 |
| Frame-by-Frame SSIM (Wang '04) | 0.812 |
| D-VIF (Sheikh '05) | 0.849 |





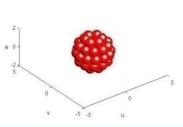
Current: Optical Flow Modeling

• Assume:

 Video segments (without scene changes) consist of *local* (*instantaneously*) translating image patches.

Model:

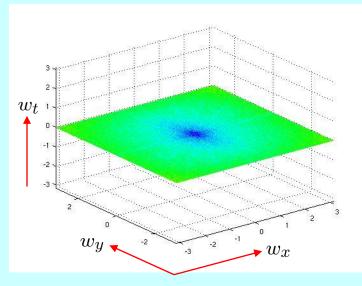
- Combines GSM model for natural images with local patch translation model: local motion induces **spatio-spectral planes of higher energy**
- **3-D Gabor filterbank** based optical flow algorithm deployed to detect motion energy







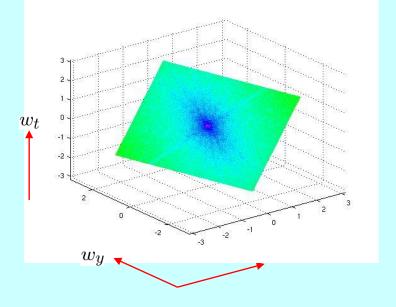
Illustration



Fourier Transform of a static sequence



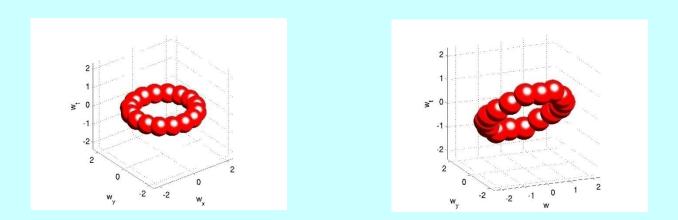
Fourier Transform of a sequence in motion





Filter Subset Selection

• Subsets of Gabor filterbank used for VQA: those that intersect the local motion plane



Filterbank automatically chosen for (left) static sequence (right) translating sequence.





Proposed Video SSIM (V-SSIM)

• We compute V-SSIM in the complex wavelet domain.

V-SSIM
$$(\vec{f}, \vec{g}) = \frac{\sum_{i=1}^{N} |f_k g_k| + K}{\sum_{i=1}^{N} |f_k|^2 + |g_k|^2 + K}$$

- Subband coefficients *f*, *g* computed from the active Gabor filters.
- V-SSIM still under development.





Proposed Video VIF (V-VIF)

• The V-VIF Index from *i*th **active** sub-band :

$$\text{V-VIF}_{i}(x) = \frac{I\left[C_{i}(x); F_{i}(x) \middle| \hat{z}_{i}(x)\right]}{I\left[C_{i}(x); E_{i}(x) \middle| \hat{z}_{i}(x)\right]}$$

- Variance field \hat{z} estimated from sub-band energies along the motion trajectories.
- Measures info the HVS can extract from the *distorted video*, normalized by the info the HVS can extract *from the reference video*.

V-VIF still under development.



Seshadrinathan & Bovik, VPQM, Jan '07



A LIVE Video Quality Database

• We have begun to create a **LIVE VQA Database** of generic power freely available to the research community.

 We shall provide subjective scores (MOS, DMOS) for the distorted videos.





Towards a Video Quality Database

- VQEG Phase-I FR-TV database has significant limitations. Most reference and distorted videos are *interlaced* - hence visual artifacts in the *reference* as well as distorted video sequences.
- **De-interlacing is inappropriate** in a VQA framework.
- The VQEG database consists *only* of compressionrelated artifacts produced by e.g., H.263 and MPEG codecs.





Towards a Video Quality Database

- Acquiring high-quality, progressive scanned, copyright free source videos is difficult. We've obtained ~ 12 HD videos.
- We've created a GUI to perform Single Stimulus Continuous Quality Evaluation (SSCQE) experiments subjects provide a *time-dependent* index of quality well suited to applications such as video monitoring and quality control.
- Our psychometric study will be done in consultation with noted visual psychologists and frequent collaborators L. Cormack and W. Geisler.
- Envision that the resulting database, with a wide diversity of distortions, will prove more challenging than current VQEG database, and will enable more rigorous performance evaluation of QA systems.





Beyond QA: Using QA Indices for Other Things

- SSIM Index is well-suited to other applications, since not specific to any receiver or transmitter models.
- We are exploring its utility for other types of signals and other applications.
- For example we have developed **automated inspection systems** based on SSIM:
 - The US Postal Service is using SSIM to evaluate letter-reading cameras.
 - The US Mint is using SSIM to detect minted coin defects.





SSIM Applications by Others

• SSIM has been used for signal fidelity/quality assessment in many applications, including

text recognition, palmprint verification, face recognition, image fusion, content retrieval/indexing, image/video compression, watermarking, denoising, color image quality, retinal and see-through wearable displays, video hashing, and visual surveillance, etc.

- In very diverse areas: digital camera design, IR imaging, MRI imaging, remote sensing, ATR, chromosome imaging, industrial control, etc.
- Deployed in popular public-domain software such as the MSU Video Quality Measurement Tool and the award-winning freeware H.264 codec x.264





What Really Excites Me

- **Perceptual optimization** using image / video quality indices!
- Much of what we have "optimally" designed over the past 30+ years should be re-examined
- Signal restoration, denoising, enhancement, reconstruction, compression, display, quantization, scaling, recognition, detection, tracking etc etc etc
- Seek optimization using accurate perceptual measures—rather than "perceptual data."





Example: Optimal Linear Image Restoration

Classic blur + noise

y = g * x + n

MMSE approach: find best linear filter that minimizes

$$E\left[\left(\hat{\mathbf{x}}-\mathbf{x}\right)^{2}\right]$$

over all

$$\hat{\mathbf{x}} = \mathbf{h} * \mathbf{y}$$





SSIM-Optimal Linear Image Restoration

• Maximum SSIM approach: find best linear filter that maximizes statistical SSIM Index:

$$Stat - SSIM(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) = \left(\frac{2\mu_{\mathbf{x}}\mu_{\mathbf{y}} + C_{1}}{\mu_{\mathbf{x}}^{2} + \mu_{\mathbf{y}}^{2} + C_{1}}\right) \left(\frac{2E\left[\left(\tilde{\mathbf{x}} - \mu_{\mathbf{x}}\right)\left(\tilde{\mathbf{y}} - \mu_{\mathbf{y}}\right)\right] + C_{2}}{E\left[\left(\tilde{\mathbf{x}} - \mu_{\mathbf{x}}\right)^{2}\right] + E\left[\left(\tilde{\mathbf{y}} - \mu_{\mathbf{y}}\right)^{2}\right] + C_{2}}\right)$$

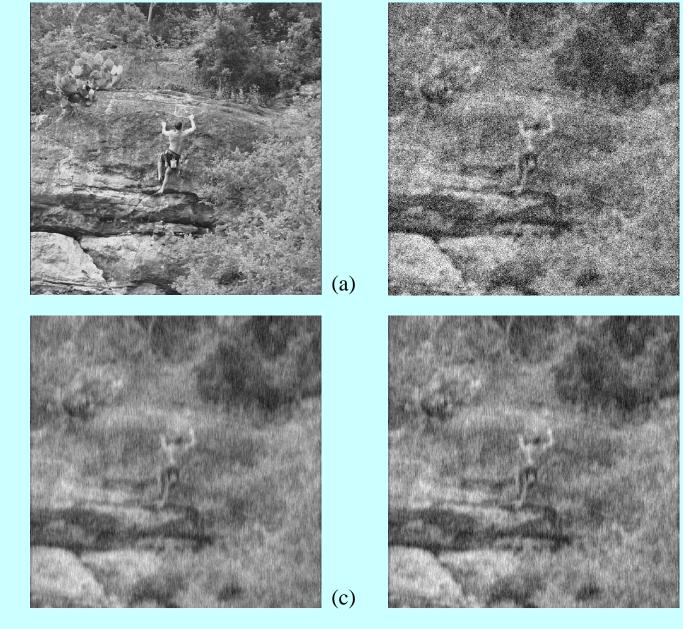
over all

$$\hat{\mathbf{x}} = \mathbf{h} * \mathbf{y}$$

• We have solved this problem in a near closed form, computationally efficient manner.







blur+noise

(b)

SSIM-optimal



MMSE



(d)

Questions?





LIVE's IQA/VQA Sponsors







