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VQEG Meeting - Boulder, Colorado, USA

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Training-based NR VQA

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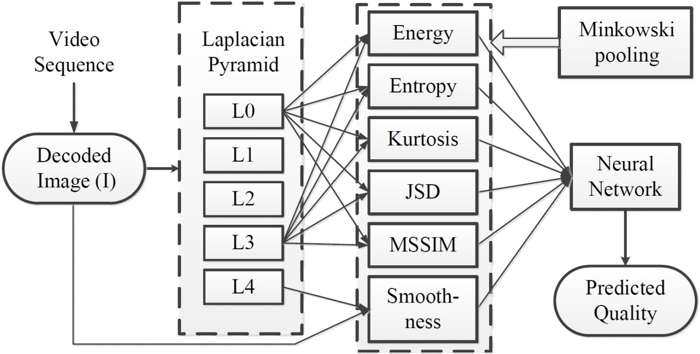

Step 1
Laplacian Decomposition

Step 2
Features Extraction

Step 3
Quality Prediction

Motivation

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Neural network: overfitting

- Large number of parameters
- Small number of videos for training

Goal and approach

- New non-linear mapping model
- Small number of parameters
- Analysis of the influence of video content

MOS VS. Entropy

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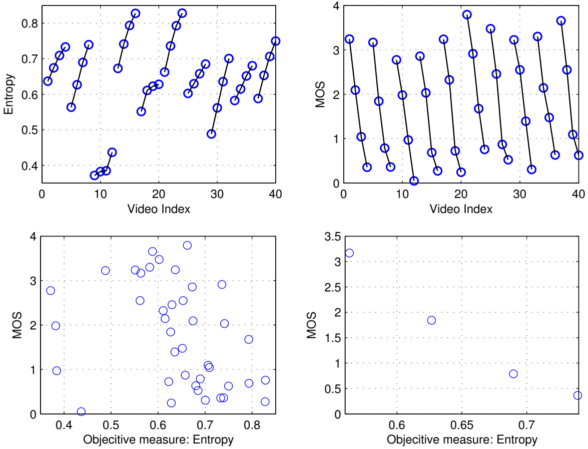
LIVE mobile video database



Notation

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Let

- one video: the nth video in the mth video set
- the predicted quality: $\hat{y}(m,n)$
- six extracted video-level features: $f_i(m,n)$, $i = 1, \cdots, 6$
- $m = 1, \cdots, M, n = 1, \cdots, N$
- M: the total number of video sets in the database
- N: the number of videos in one set

Non-linear mapping

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1) Global linear function

$$y'(m,n) = \Sigma_i w_i f_i(m,n), \tag{1}$$

2) Local alignment

$$y''(m,n) = s(m)y(m,n) + b(m), \tag{2}$$

3) Quality calibration

$$\hat{y}(m,n) = g(y''(m,n)), \tag{3}$$

$$g(x) = \frac{\beta_1 - \beta_2}{1 + \exp(-(x - \beta_3)/|\beta_4|)} + \beta_2$$

Prediction: scale s and offset b

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- Prediction of the offset b

$$\hat{b}(m) = as(m), \quad m = 1, \cdots, M. \tag{4}$$

- Prediction of the scale s

$$\hat{s}(m) = \alpha_3 f_2^3(m) + \alpha_2 f_2^2(m) + \alpha_1 f_2(m) + \alpha_0, \tag{5}$$

for $m = 1, \cdots, M$, and $f_2(m)$ is the video-level entropy of the reference video in the mth video set.

Video database

IRCCyN/IVC influence content video VGA database

- 60 sets of videos ($M = 60$)
- 5 H.264 videos in each ($N = 5$)
- Resolution: 768×432
- The mean opinion score (MOS): $[0, 5]$
- H.264/SVC coding without transmission errors

Before and after supervised alignment

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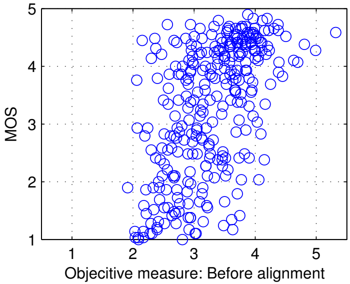
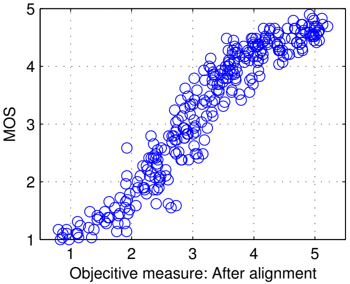
Scatter plots





Parameter prediction

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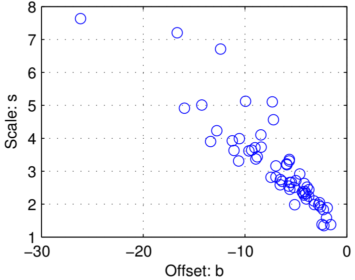
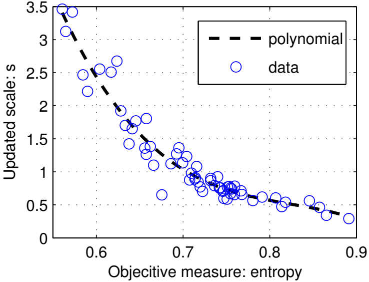
Scatter plots





Before and after calibration

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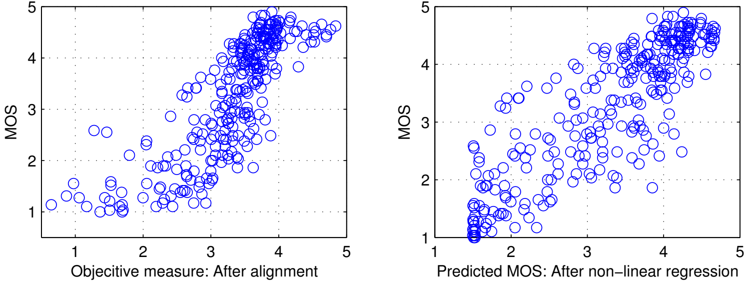
Scatter plots



Performance Evaluation

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	LCC	SROCC	RMSE	MAE
Before alignment	0.3873	0.3698	1.8813	1.4919
After alignment	0.7996	0.8475	0.6985	0.5906
After regression	0.8554	0.8475	0.5894	0.4630
Supervised	0.9667	0.9581	0.2911	0.2196

- LCC: the Linear (Pearson's) Correlation Coefficient
- SROCC: the Spearman's Rank Ordered Correlation Coefficient
- RMSE: the Root Mean Squared Error
- MAE: the Mean Absolute Error

Summary

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Conclusions

- Studied the influence of video content on NR VQA
- Proposed a non-linear mapping strategy for NR VQA
- Improved the performance by designing local alignment
- Required small number of parameters
- Avoided overfitting in training-based methods

Limitation and Future work

- Only test in one video database with one type of distortion
- Develop more methods for local alignment according to video content

For more information:

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Read

K. Zhu, K. Hirakawa, V. K. Asari, and D. Saupe,“A no-reference video quality assessment based on Laplacian pyramids”, IEEE International Conference on Image Processing, Melbourne, Australia, Sep. 2013.

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Appendix

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Backup Slides

Intra-subband features

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Let us view the subband coefficients in L_n as stationary random processes, where the random variable $X = L_n(i,j)$ have the same probability mass function $p(x)$.

1) Energy

$$E_n = \log_{10}\left(\Sigma_i \Sigma_j L_n^2(i,j)\right)$$

2) Entropy

$$H_n(X) = -\Sigma p(x) \log p(x)$$

3) Kurtosis

$$\kappa_n(x) = E(x-\mu_x)^4/\sigma_x^4$$

where

- x is the intensity, $p(x)$ is the probability mass function
- μ_x is the mean of x, and σ_x is the standard deviation

Inter-subband features

1) JSD (Jensen Shannon divergence)
A measure of the distance between two probability distributions

$$\mathrm{KLD}(p||q) = \sum p(x) \log(p(x)/q(x))$$
$$\mathrm{JSD}(p||q) = \frac{1}{2}(\mathrm{KLD}(p||r) + \mathrm{KLD}(q||r))$$

where

- $r(x) = (p(x) + q(x))/2$
- $p(x)$ and $q(x)$ as two probability mass functions of two images

Inter-subband features:

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The SSIM: Structural SiMilarity Index (Z. Wang, 2004)

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

2) MSSIM (the mean structural similarity index)

- $\mathrm{MSSIM}(L_n, L_m)$: the mean of SSIM index map
- quantifies the dependency between L_n and L_m

3) Smoothness

a measure of the relative size of flat area

- S_{SSIM} is the SSIM index map between I and L_{N-1}
- the local region is flat when the SSIM index is $\geq T_0$
- T_0 is set to 0.95 in the experiment