Modeling Sparse Spatio-Temporal Representation for No-Reference Video Quality Assessment

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Introduction

- Video content generation and consumption continues to grow exponentially
- Objective Video Quality Assessment (VQA) an indispensable tool for content management
- No-reference VQA (NRVQA) especially important when pristine source unavailable - a very common occurrence in reality
- We present a sparsity based NRVQA algorithm

Background

- NRVQA algorithms rely on finding distortion discriminative features - handcrafted and machine learnt [1, 2, 3]
- Supervised learning of functional relationships between features and Difference Mean Opinion Scores (DMOS)
- The Human Visual System (HVS) hypothesized to sparsely represent visual stimulus [4]
- Several sparsity based image QA algorithms proposed [5]
  - Hypothesis is that sparse representations are distortion discerning
- Proposed sparsity based NRVQA algorithm among the first of its kind

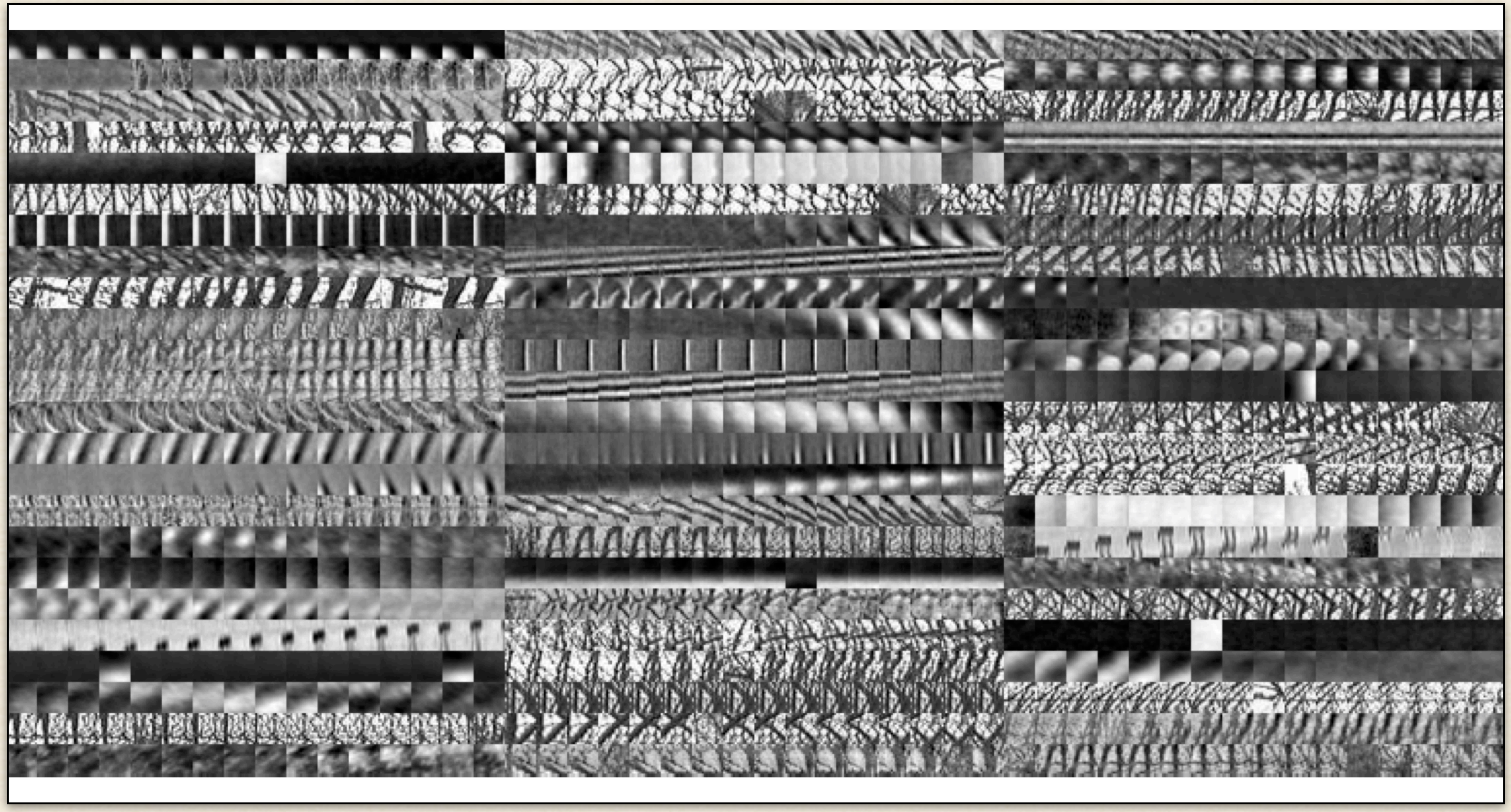
Sparse Representation of Spatio-Temporal Volumes

- A spatio-temporal volume is expressed in terms of a linear combination (using a_i) of atomic volumes (ϕ_i) from an overcomplete dictionary:

$$V(x,y,t) = \sum_i a_i \phi_i(x,y,t)$$

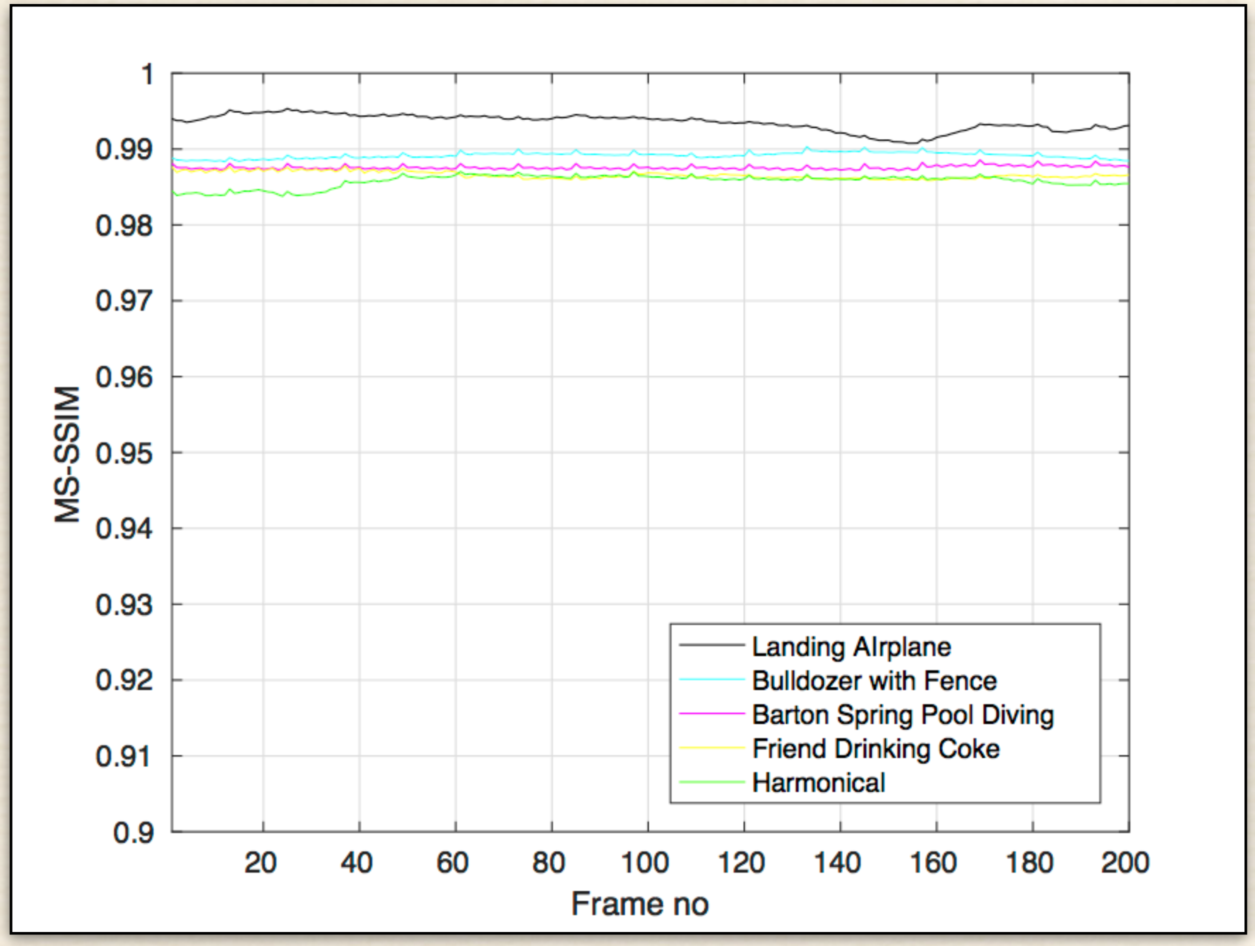
- The dictionary of video volumes is constructed using pristine video volumes
- The KSVD algorithm [6] used for t construction
  - Volume unwrapped into a vector and standard approach followed
  - Unwrapping in a particular order retains spatio-temporal correlation
  - Dictionary size $N \times 2N$
  - Various volume sizes (x, y, t) considered: **5 x 5 x 3** to **16 x 16 x 16**
  - Pristine videos from LIVE SD Video Database [8]

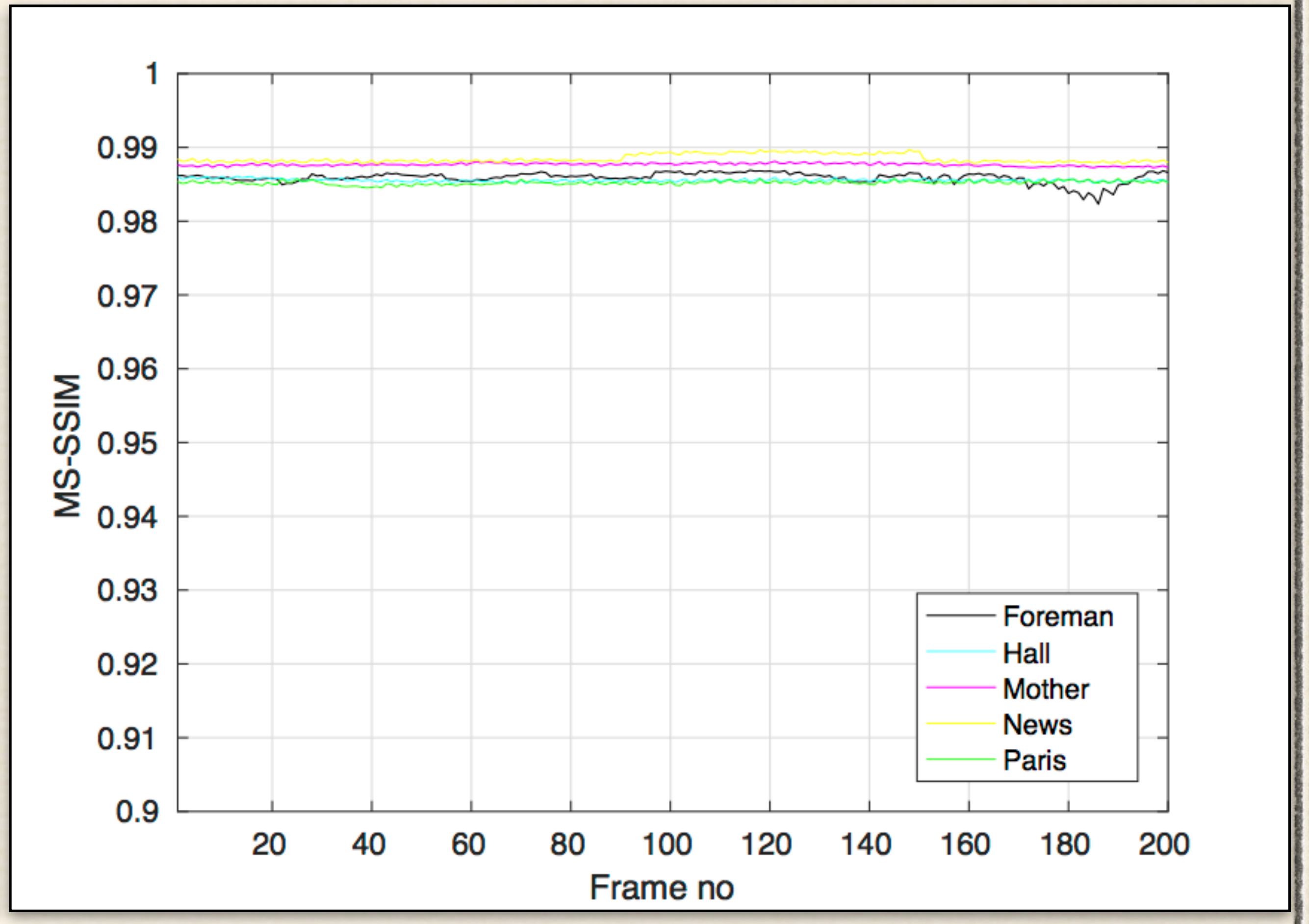
72 atoms from Dictionary of size16 x 16 x 16



Robustness and Reliability of Dictionary

- Volume size of **5 x 5 x 3** was found to give best reconstruction performance. Plots show frame-wise MS-SSIM index [7]





- LIVE Mobile HD Database [9]

EPFL Database [10]

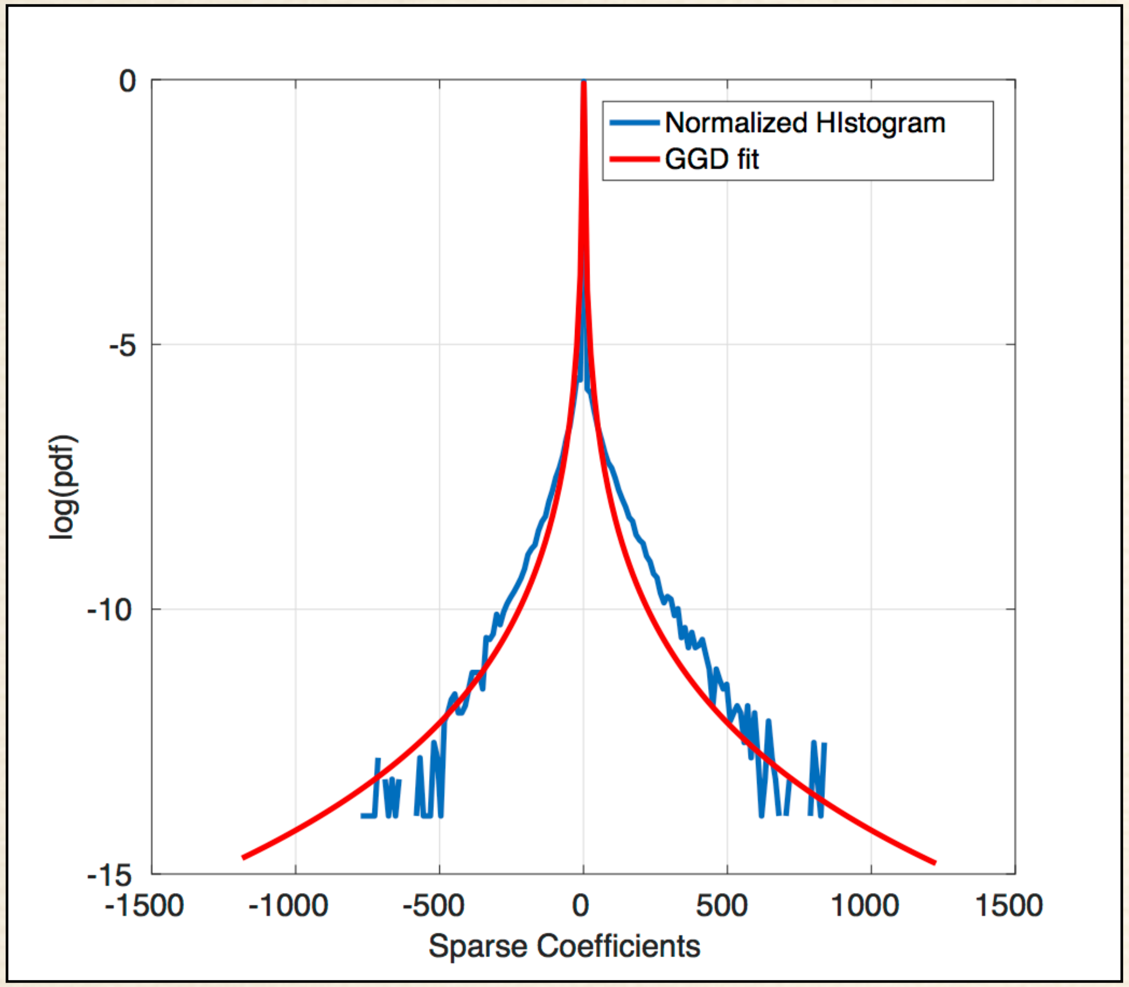
Proposed NRVQA Algorithm

- NRVQA algorithm uses dictionary with atom size **5 x 5 x 3**
- The histogram of sparse coefficients corresponding to each atom is modeled using a generalized Gaussian distribution:

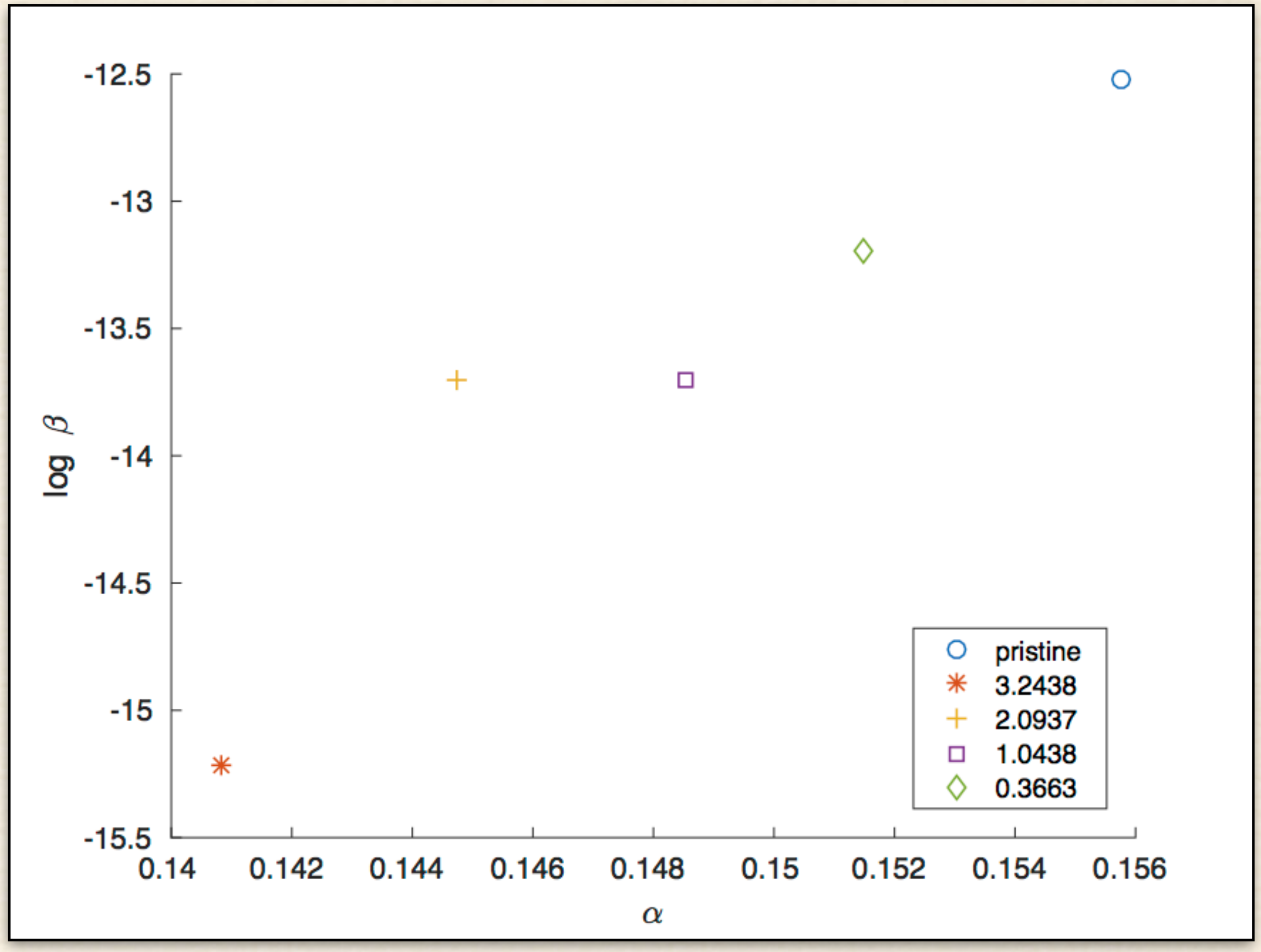
$$f(x;\alpha,\beta)=\frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)}exp\left(-\frac{|x|}{\beta}\right)^{\alpha}$$

- The model parameters(α,β) serve as excellent distortion discriminatory features
- These features are used for supervised learning of DMOS labels using support vector regression (SVR)

GGD Model and its Effectiveness on the LIVE Mobile Database [10]



Model fit for Atom 1



Distortion discrimination (legend DMOS)

Evaluation Databases

Database	# Videos (Distorted + Reference)	Frame Rate (FPS)	Resolution	Distortions
LIVE SD [8]	150 + 10	25/50	768 x 432	MPEG2, H264, IP, Wireless
EPFL SD [9]	144 + 12	30	352 x 288/ 704 x 576	Packet loss
LIVE Mobile HD [10]	160 + 10	30	1280 x 720	Compression, Rate adaptation, Temporal dynamics, wireless

Results on SD Databases

	LIVE SD [8]		EPFL SD [9]	
	LCC	**SROCC**	**LCC**	**SROCC**
NIQE [11]	0.2668	0.2250	0.5160	0.4998
VIIDEO [1]	0.6510	0.6240	0.1840	0.2025
Video BLIINDS [2]	0.8810	0.7590	0.7520	0.8070
FLOSIM-NR [3]	0.6076	0.5864	0.8915	**0.8961**
Lie et al. [12]	**0.8910**	**0.7820**	0.8050	0.7960
Proposed	*0.7082*	*0.6621*	***0.9107***	*0.8764*

Results on HD Database

	LIVE Mobile HD [10]		LIVE Tablet HD [10]	
	LCC	**SROCC**	**LCC**	**SROCC**
NIQE [11]	0.7560	0.7410	0.7569	0.7559
VIIDEO [1]	0.2451	0.2164	0.5430	0.5027
Video BLIINDS [2]	0.3734	0.4392	-	-
FLOSIM-NR [3]	0.8450	0.8352	0.9140	0.8647
Proposed	***0.9253***	***0.9007***	***0.9686***	***0.9382***

Results: Computational Cost

	LIVE SD [8]	
	Time/Video (secs)	**Improvement (%)**
Video BLIINDS [2]	311	90
VIIDEO [1]	132	77
FLOSIM-NR [3]	43	28
Proposed	***31***	-
Tested on: 3.1 GHz Intel Core i7, 16 GB RAM, Ubuntu 16.04		

Conclusions

- Developed a NR-VQA algorithm based on natural video statistical features
- A spatio-temporal dictionary designed for sparsely representing natural video volumes
- Modeled sparse coefficients using a GGD
- GGD model parameters able to discern spatial and temporal distortions jointly
- A simple and computationally efficient NR-VQA algorithm dubbed SParsity based Objective VIdeo Quality Evaluator (SPOVIQE)
    - Supervised learning (model parameter features, DMOS labels) using SVR
- SPOVIQE has very competitive performance on the LIVE SD, EPFL-SD and LIVE HD databases in addition to having low computational complexity

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