Correlating Video Quality Metrics to User Experience: an Event-based Approach

- Master's Thesis Defense -

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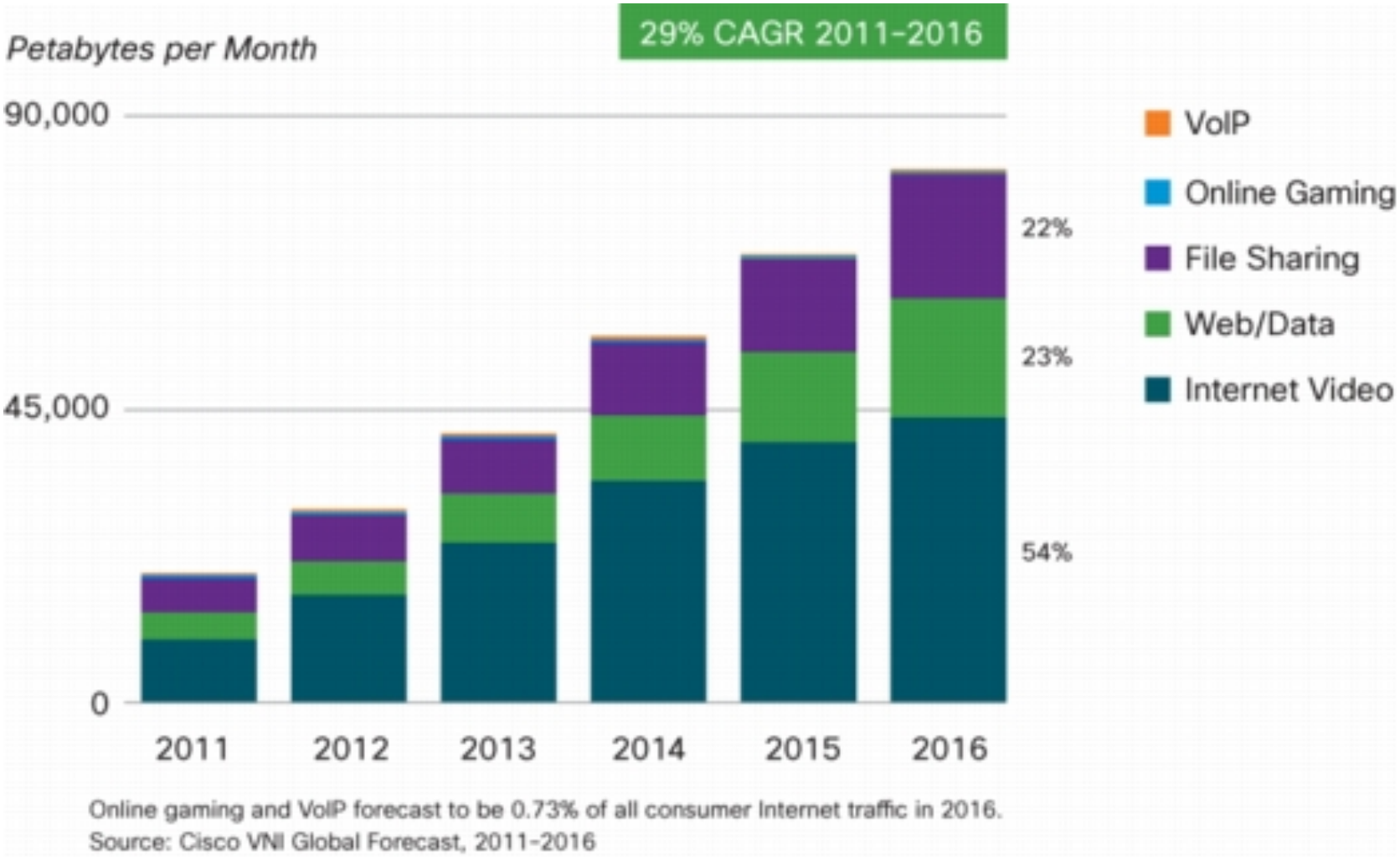
Contents

- Introduction & Motivation
- Background & Related Work
- Event-based user experience assessment
  - Classification of defect events
  - Event to experience correlation
- Validation
- Conclusion & Future Work

Internet Traffic Trend

❖ Multimedia will dominate IP traffic



http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537/ns705/ns827/VNI_Hyperconnectivity_WP.html

The Management Challenge

❖ Management of multimedia services

- For content providers, ensuring service quality is important (*service differentiator to attract and retain customers*)
- To be specific, network service providers need to **assess**, **manage**, and **improve** user perceptual experience

❖ User experience of video quality

- Compared to quality of service (QoS), quality of experience (QoE) considers human perception
- Human vision system (HVS) is very complicated to model, i.e. user's preference for video content, user's interest of frame region, etc.

Current Limitations

❖ User feedback is impractical in reality

- Well-controlled user experiment with a wide variety of test elements is not easy to design or administer
- Users cannot be bothered with giving truthful feedback each time

❖ Limitation of current objective measurements

- Temporal factors are missed, i.e. the peak signal-to-noise ratio (PSNR)
- Content-related factors are missed
- Events play a crucial role in human experience (*not reflected*) [J. M. Zacks et al., 2010]

Objectives

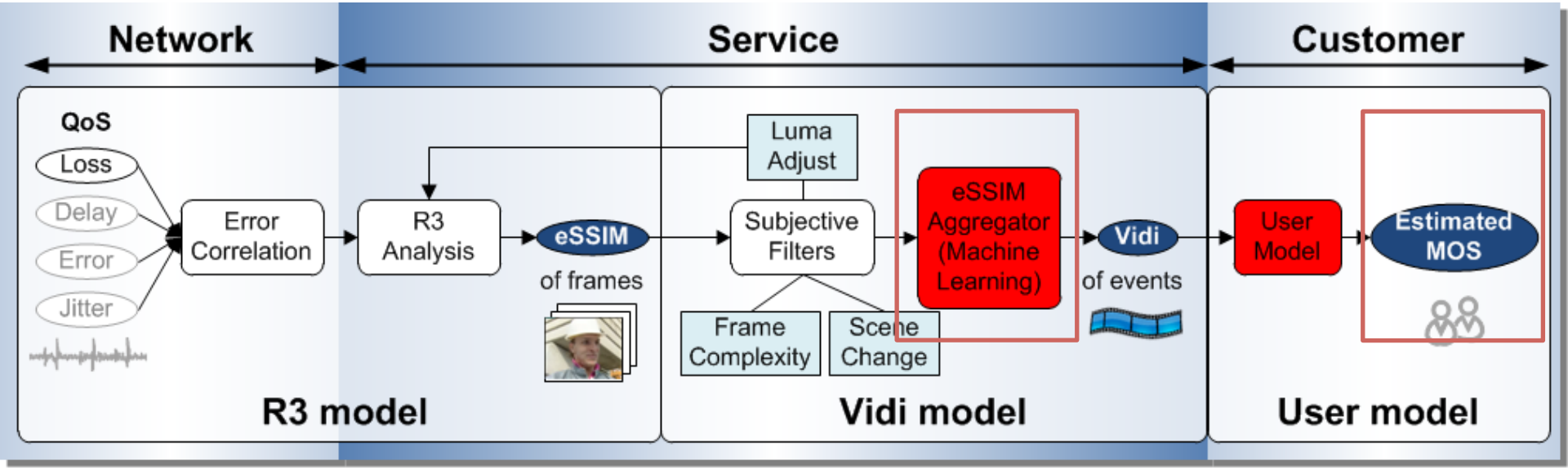
- Propose an approach for correlating video quality metrics to user experience
  - Accurate and efficient
- Consider event-based human experience
  - How to identify/segment defect events in videos
  - How to classify defect events
  - How to correlate events to user experience

Contributions

- An event-based approach for correlating video quality metrics to user experience
  - The first (to the best of my knowledge) to consider that human experience is event-based
  - Event classification: accurate and efficient classification of defect events (eSSIM Aggregator)
  - Event-to-experience correlations: correlate different event types to user experience by constructing event-specific user models.

❖ VIDAR: video quality analyzer in real-time [A. Kwon et al., 2012]

- Correlate network performance to user experience
- Structure Similarity (SSIM) – frame quality metric [Z. wang et al., 2004]



Machine Learning (ML)

Mean opinion score (MOS)

Related Work

❖ Statistical approach

- Rely on one or two salient perception characteristics
- Mean square error (MSE) [A. Bhat et al., 2009]
- PSNR [O. Nemethova et al., 2006]
- Content factors are missed

❖ Machine learning approach

- Decision tree [V. Menkovski et al., 2009]
  - Data instances: video spatial information, video temporal information, frame rate and bit rate
  - Result: “YES” or “NO”

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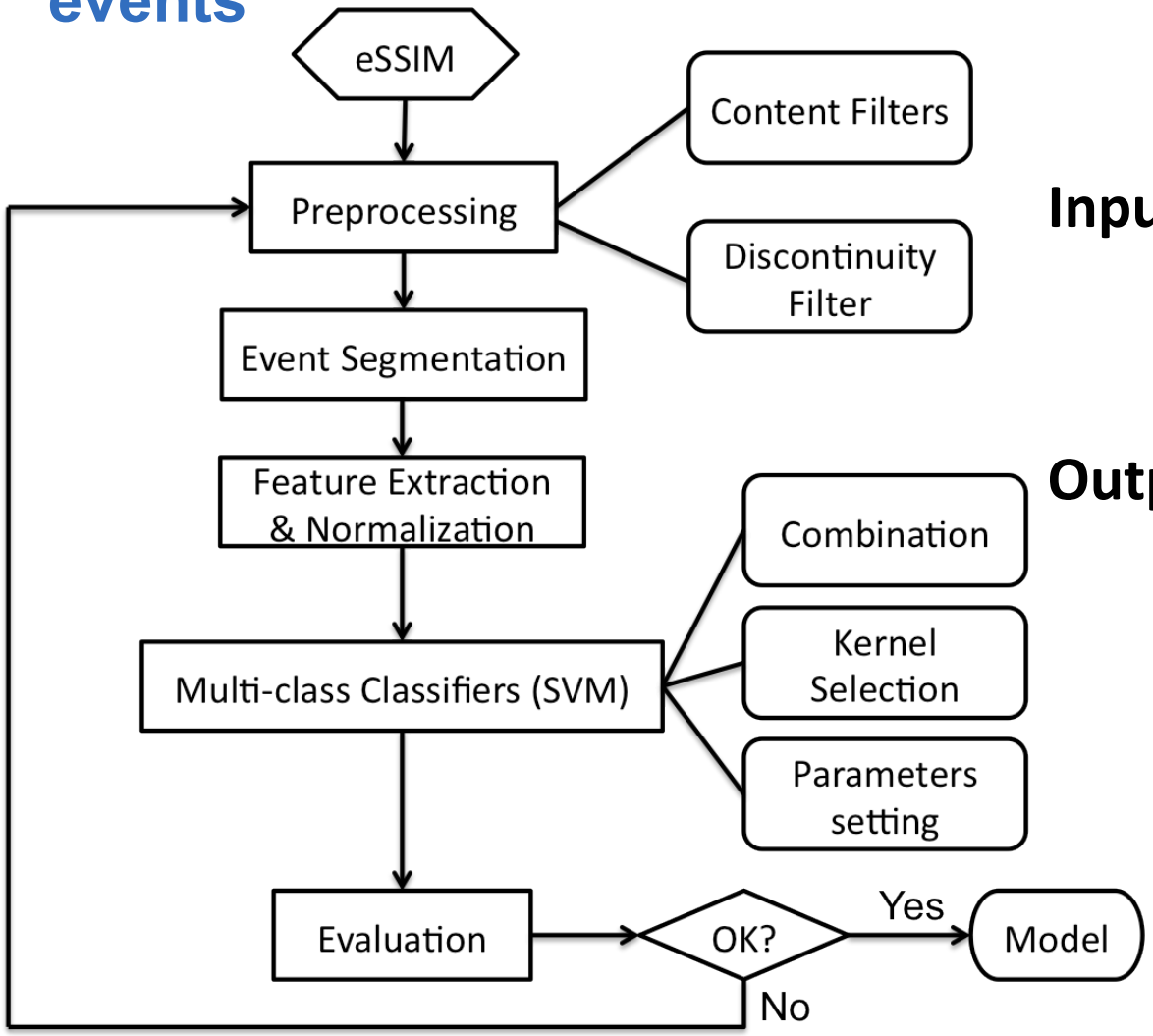
Process Flow of eSSIM Aggregator

- **eSSIM aggregator for detecting and classifying defect events**



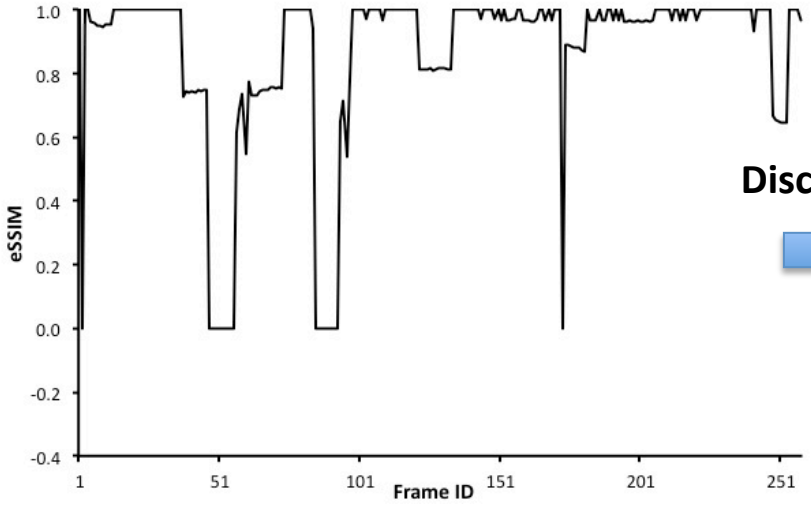
Input: eSSIM of frames

Output: defect events

Preprocessing (Discontinuity Filter)

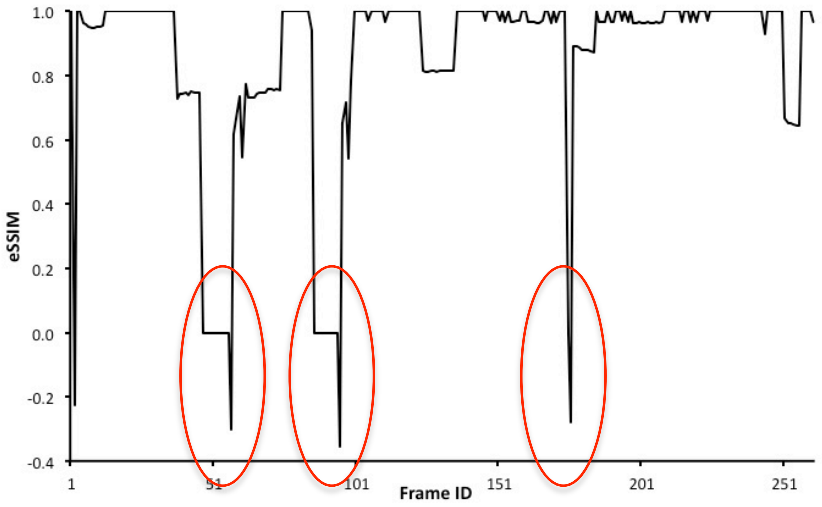
- Meaning of eSSIM values
- Show the intensity of discontinuity in the video

eSSIM of frames



Discontinuity filter

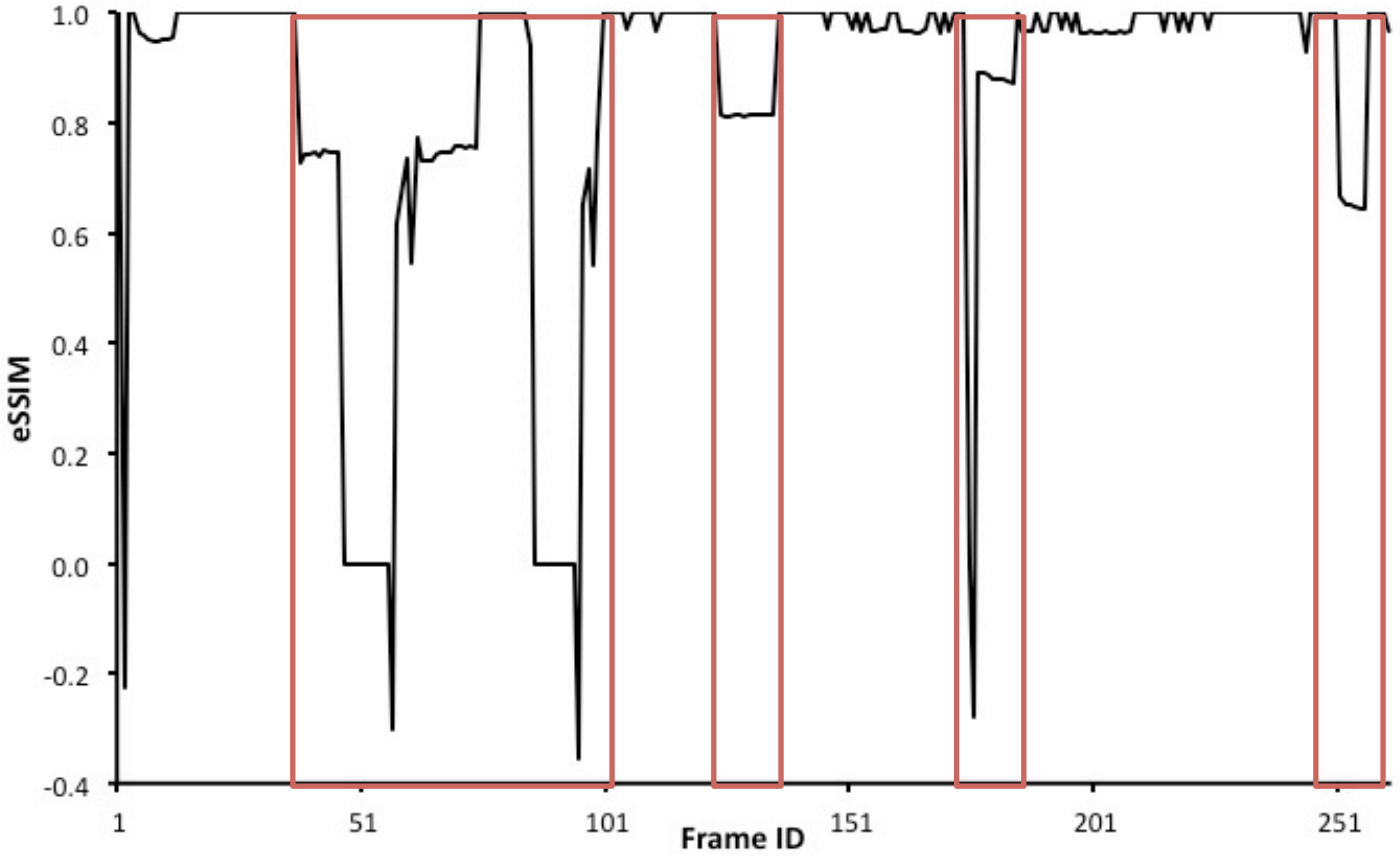
eSSIM of frames with discontinuity mark



Foreman, GOP = 12, 2% GE loss model

❖ A set of rules to segment defect events

- i.e. the first 10 frames of each video are ignored



Foreman, GOP = 12, 2% GE loss model

Feature Extraction and Normalization

❖ Purposes of extracting features

- To distinguish different types of defect events
- Reduce the dimension and input of ML classifiers

❖ Features extracted

- ***Mean (μ)*** **and** ***standard deviation (δ)***
- ***Minimum***: the minimum e***SSIM*** value of an event
- ***Defective ratio***:

$$ratio = \frac{N_{eSSIM<0.95}}{n}.$$

- Severity of dropped and duplicated frames:

$$severity = \frac{N_{eSSIM\leq 0.0}}{n}.$$

- Skewness: measure of the asymmetric of the probability distribution of event data
- Kurtosis: measure of whether the distribution is peaked or flat, relative to a normal distribution

❖ Feature normalization

- Middle-range normalization: [-1, 1]
- Mean-std normalization: mean = 0, std = 1

Multi-class Classifiers - Types of Defect Events

- Distortion: a series of frames containing perceivable distortions
- Glitch: a series of frames, where distortion is short and slightly perceivable
- Freezing: a series of duplicated frames
- Video samples of defect events

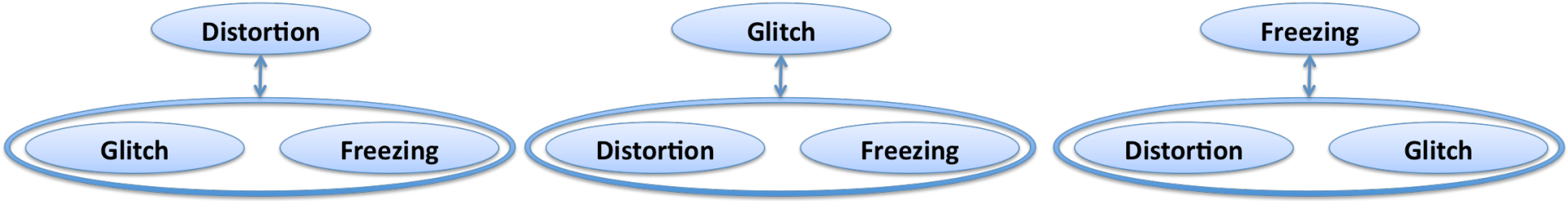
Multi-class Classifiers

❖ Support vector machine (SVM)

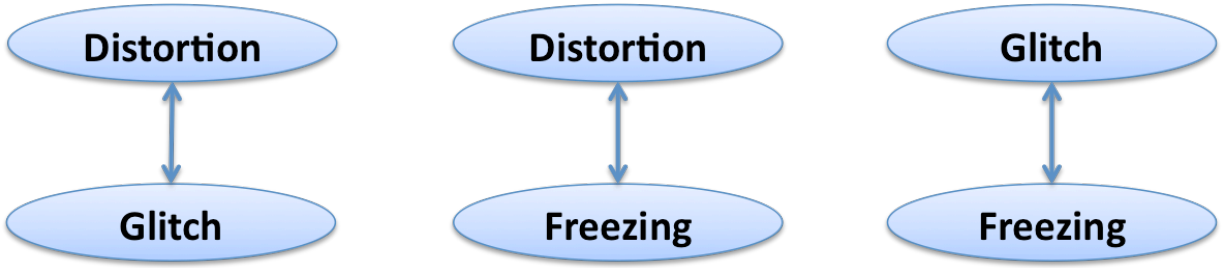
- Multi-dimension and continuous features
- Nonlinear situations

❖ Multi-class classification with SVM

- Combination of binary SVM classifiers
  - One-versus-all:



  - One-versus-one:



Correlating event metrics to User Experience

- **Correlational models for predicting user MOS from event metrics**

- **Intensity features for Distortion**

  {*μ*, *ratio*, *frame complexity*, *motion speed*}

- **Intensity features for Glitch**

  {*μ*, *ratio*, *frame complexity*, *motion speed*}

- **Intensity features for Freezing**

  {*the time duration*, *discontinuity intensity*}

- **Artificial neural network (ANN)**
  - **No readily discernable patterns statistically**
  - **ANN shows good accuracy**

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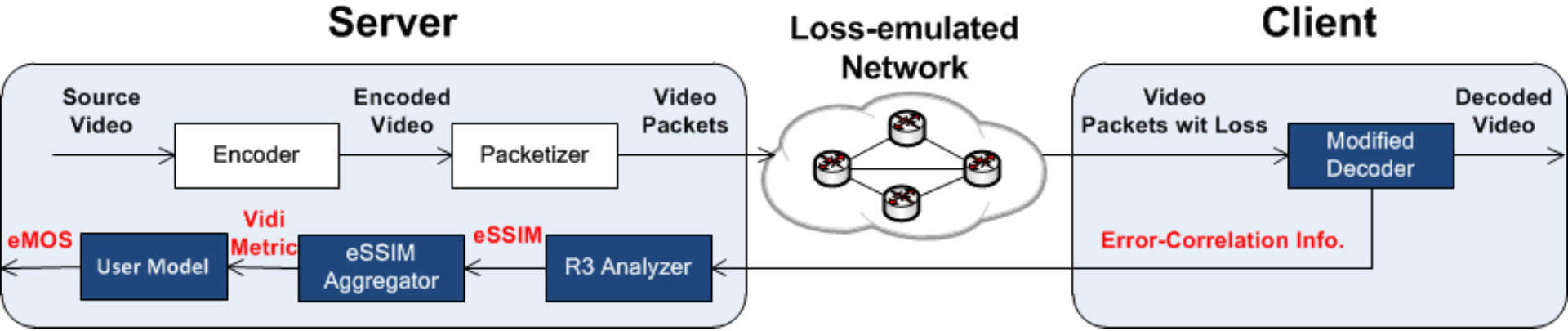
❖ Experiment setup



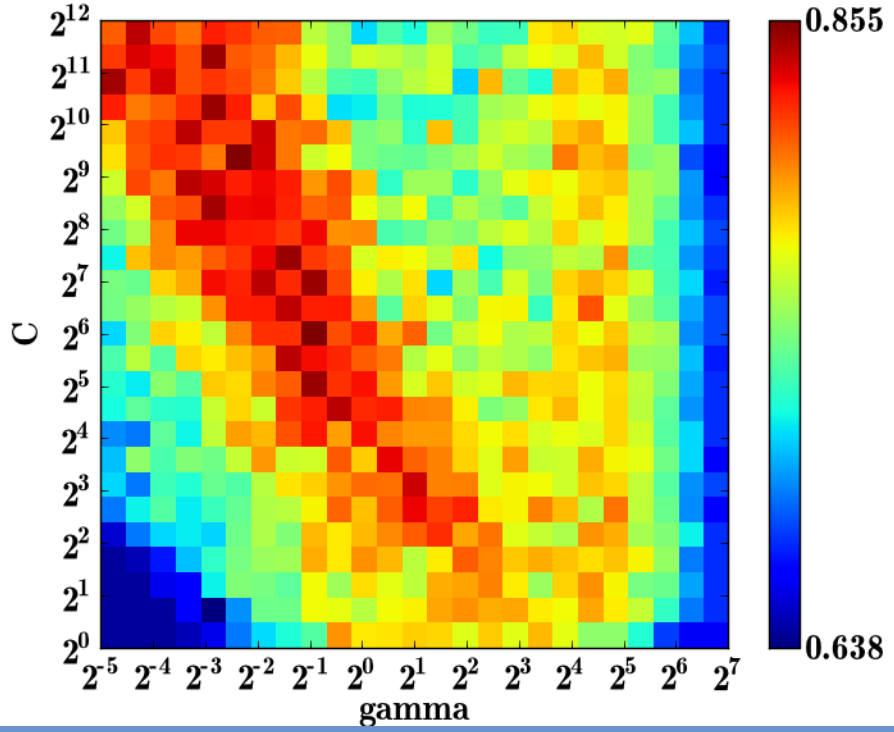
Name	Number of Scene Cuts	Scene Moving Speed	Object Moving Speed	Average Frame Complexity	Content
Bus	0	Middle	Fast	27.95	Bus
Container	0	No	Slow	16.18	Ship with containers
Flower	0	Middle	Slow	22.14	Flower and house
Football	0	Fast	Fast	11.96	Football players
Foreman	0	Slow	Slow	18.73	Portrait and construction
Mother &Daughter	0	No	Slow	12.60	Portrait
Stefan	0	Slow	Middle	23.62	Tennis player
Inception	6	Fast	Fast	18.00	Portrait, construction and etc.

Type	Number
Distortion	**151**
Glitch	**39**
Freezing	**48**
Total	**238**

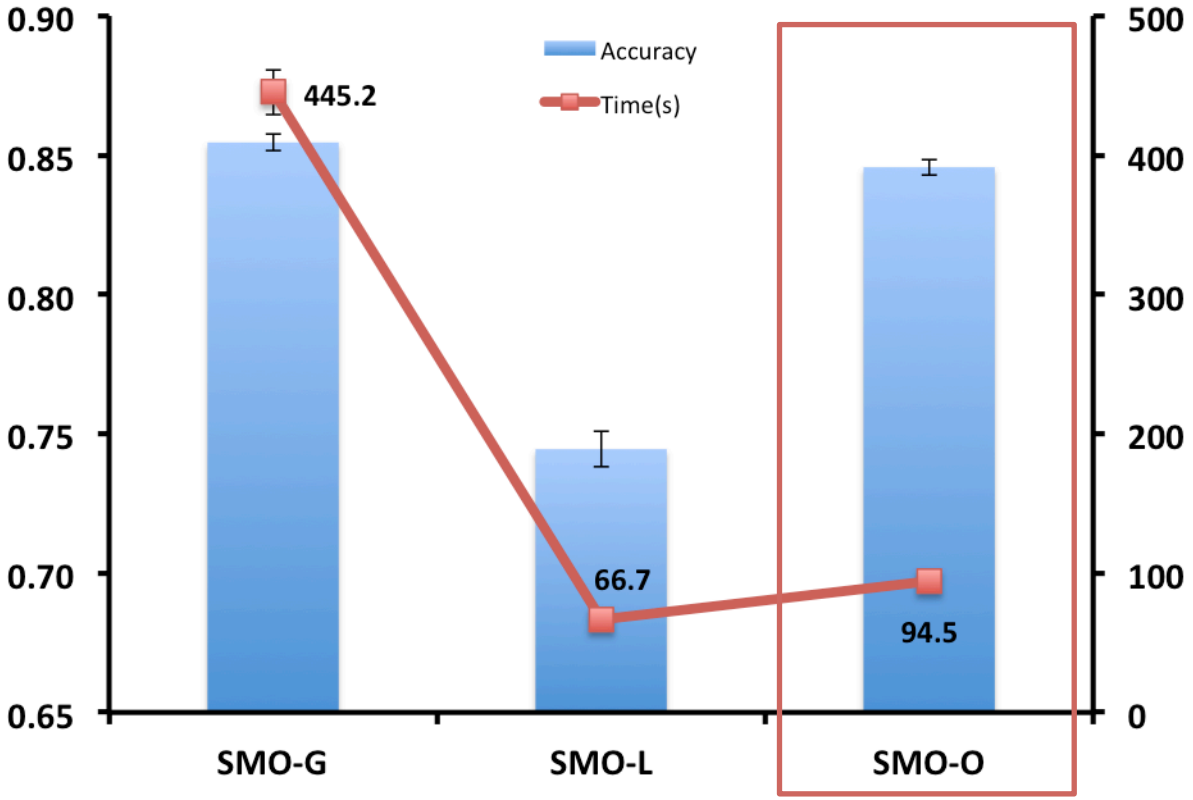
Kernel Selection and Parameter Setting (SVM)

- **Sequential minimal optimization (SMO) (J. Plat et al., 1998)**
  - An algorithm for efficiently solving the optimization problem that arises during t training of SVMs
- **Kernel selection**
  - Linear kernel
  - Radial basis function (RBF) kernel
- **Parameter setting (RBF)**
  - Grid search
  - Optimized method (S. Keerth et al., 2003)

1. SMO-L: SMO with Linear kernel
2. SMO-G: SMO with RBF kernel, and Grid search for parameters
3. SMO-O: SMO with RBF kernel, and Optimized method for parameters



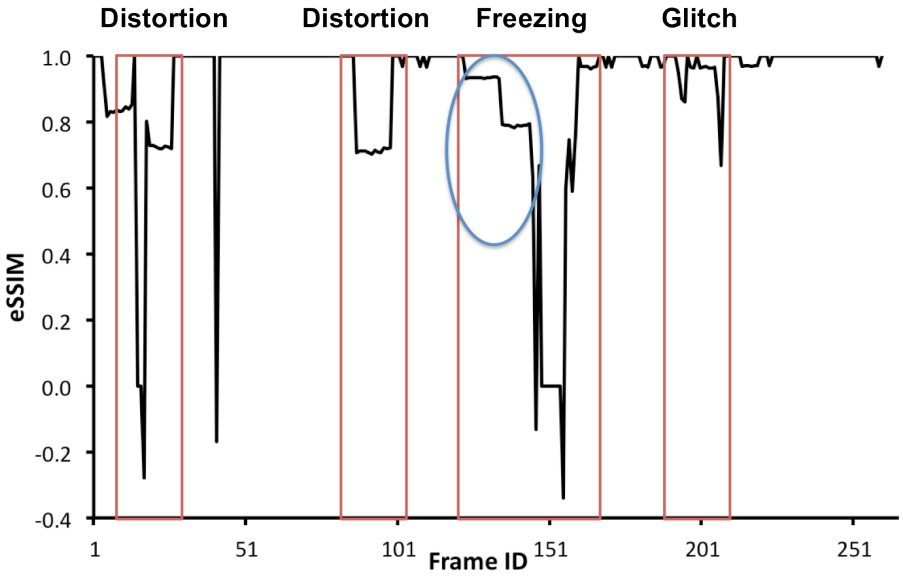
❖ Efficiency of multiclass classification



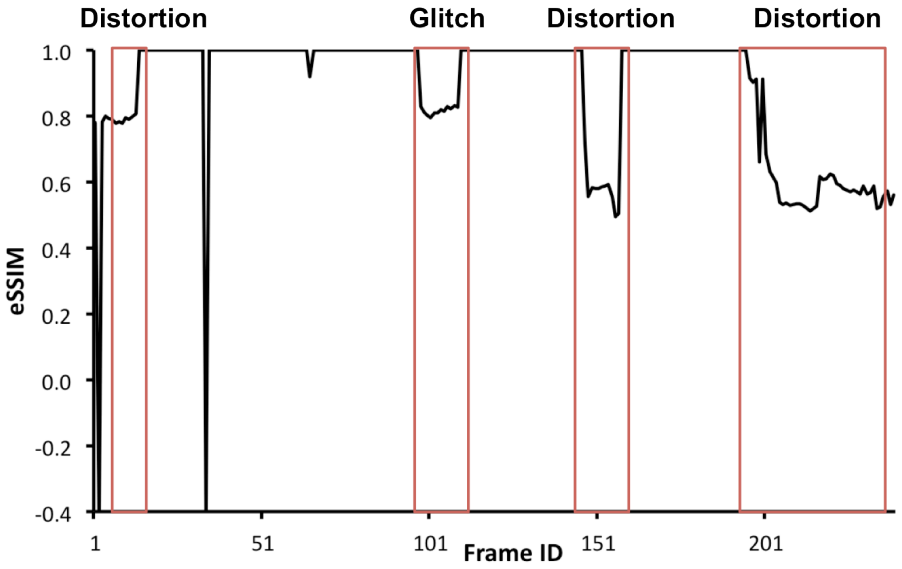
Experiment Result – eSSIM Aggregator (2/3)

❖ Classification result of each binary classifier

	Distortion vs. *Glitch*	*Distortion* vs. *Freezing*	*Glitch* vs. *Freezing*
Accuracy	92.04%±0.24%	85.38%±0.32%	97.18%±0.21%



Foreman, GOP = 12, 2% GE loss model, Frame complexity = 18.73



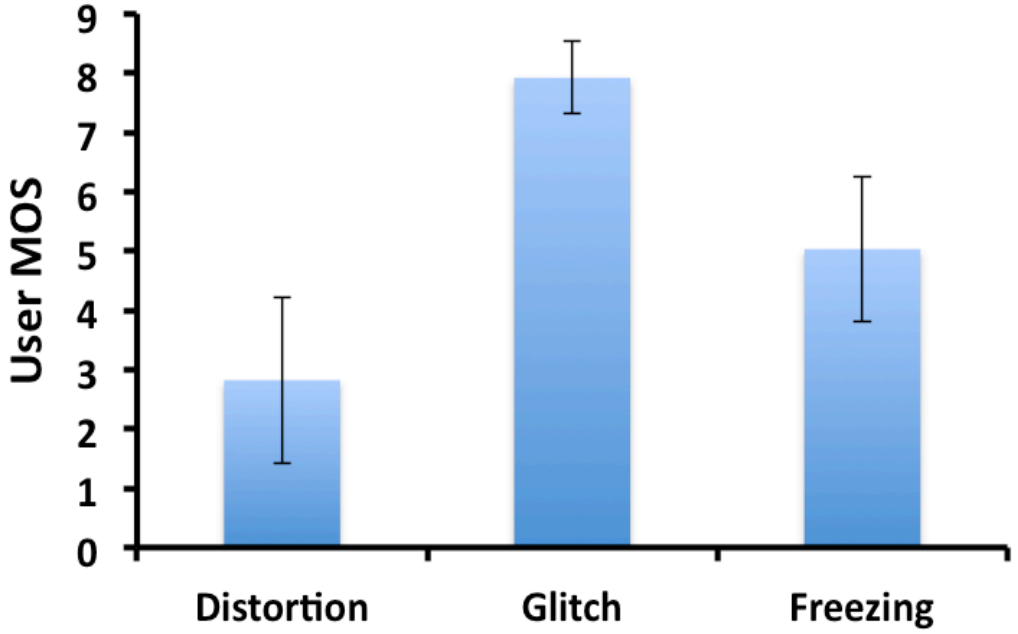
Flower, GOP = 12, 2% uniform loss model, Frame complexity = 22.14

Experiment Result – User Model (1/2)

❖ Subjective testing of user model

MOS	1, 2	3, 4	5, 6	7, 8	9, 10
Quality	Bad	Poor	Fair	Good	Excellent
Impairment	Very annoying	Annoying	Slightly annoying	Perceptible but not annoying	Imperceptible

❖ Average user MOS of defect events



MOS range of Distortion: 1, 2, 3, 4, 5

MOS range of Glitch: 6, 7, 8, 9

MOS range of Freezing: 3, 4, 5, 6, 7

❖ Classification result of user MOS on Distortion

Classified MOS

User MOS

	1	2	3	4	5
1	1	10	4	0	0
2	11	11	11	0	1
3	2	13	21	2	1
4	0	1	5	7	0
5	0	3	11	1	0

(a) {*μ*, *ratio*}

Classified MOS

User MOS

	1	2	3	4	5
1	3	10	2	0	0
2	4	17	11	1	1
3	1	11	19	6	2
4	0	2	6	4	1
5	0	3	8	4	0

(b) {*μ*, *ratio*, *frame complexity*}

Classified MOS

User MOS

	1	2	3	4	5
1	3	8	4	0	0
2	5	17	11	0	1
3	0	10	21	5	3
4	0	2	4	5	2
5	0	2	8	3	2

(c) {*μ*, *ratio*, *frame complexity*, *motion speed*}

	Exact	Drift ±1
(a)	34%	79%
(b)	37%	83%
(c)	41%	83%

Conclusion

❖ Summary

- An event-based model to correlate video quality metrics to user experience, using ML
- Event classification and event-to-experience correlations

❖ Contribution

- The first (to the best of my knowledge) to consider that human experience is event-based
- Event classification (eSSIM aggregator)
  - Provides an accurate classification of defect events with low training time
- Relating to user experience
  - Shows a strong correlation between key features (specific to each event type) and user MOS
- A good method for problem decomposition

Future Work

❖ User MOS estimation for entire video session

- Current user MOS estimation is at the event level
- A number of psychological theories will be used for modeling the complicated human perception system

❖ Reference model of user perception

- Find common response among users to generate reference model
- Identify key user-specific features that specialize reference model to individual user (or groups of like-minded users) MOS


Thank You!

Reference

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4) A. Kwon, J. Xiao, S.-S. Seo, J. W.-K. Hong, and R. Boutaba, "The impact of network performance on perceived video quality and user experience in H.264/AVC," in IEEE/IFIP Network Operations and Management Symposium (NOMS), mini-conference, April 2012.
5) A. R. Reibman and D. Poole, "Predicting packet-loss visibility using scene characteristics," in Packet Video 2007, pp. 308-317, November 2007.
6) G. W. Cermak, "Videoconferencing service quality as a function of bandwidth, latency, and packet loss," Verizon Laboratories, T1A1.3/2003-026, 2003.
7) J. M. Zacks, "How we organize our experience into events," American Psychological Association, 2010
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Related Work – Machine Learning Techniques

❖ Performance of ML

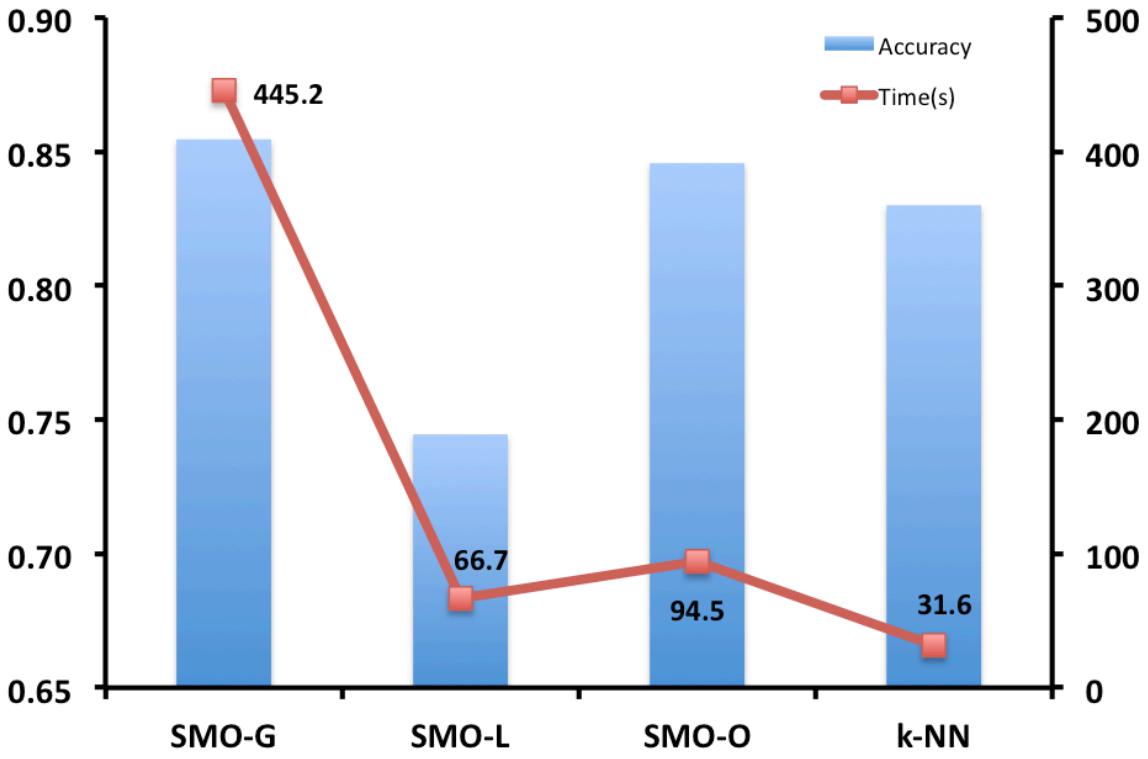
- **Accuracy**: A strong correlation between the input parameters (i.e., **features**) and the output result
- **Efficiency**: The number of features should be small and indicative

❖ Comparison of supervised ML algorithms

- Logic-based algorithms, i.e. decision tree
  - Do not perform well with numerical features
- Perceptron-based algorithms, i.e. artificial neural network
  - Inefficient with the presence of irrelevant features
- Statistical learning algorithms, i.e. k-nearest neighbor (k-NN)
  - Very sensitive to irrelevant features
- Support vector machine (SVM)
  - Performs well with multi-dimension and continuous features, as well as when a nonlinear relationship exists among the input and output features

❖ Event segmentation

- **Rationales:**
  - Human experience is event-based
  - The length of event can be scalable and the boundary between events can be coarse
- **Rules:**
  - The minimum length of a defect event is 10
  - The maximum length of a defective event is 100, about 3 seconds
  - The minimum length of boundary between two events is 10
  - When *eSSIM* >= 0.95, distortion is too small to be perceived. Therefore, we regard these frames as normal ones with *eSSIM* = 1
  - The first 10 frames of each video are ignored, because they can be counted as frames after a scene change


0.90
0.85
0.80
0.75
0.70
0.65
500
400
300
200
100
0
Accuracy
Time(s)
445.2
66.7
94.5
31.6
SMO-G
SMO-L
SMO-O
k-NN

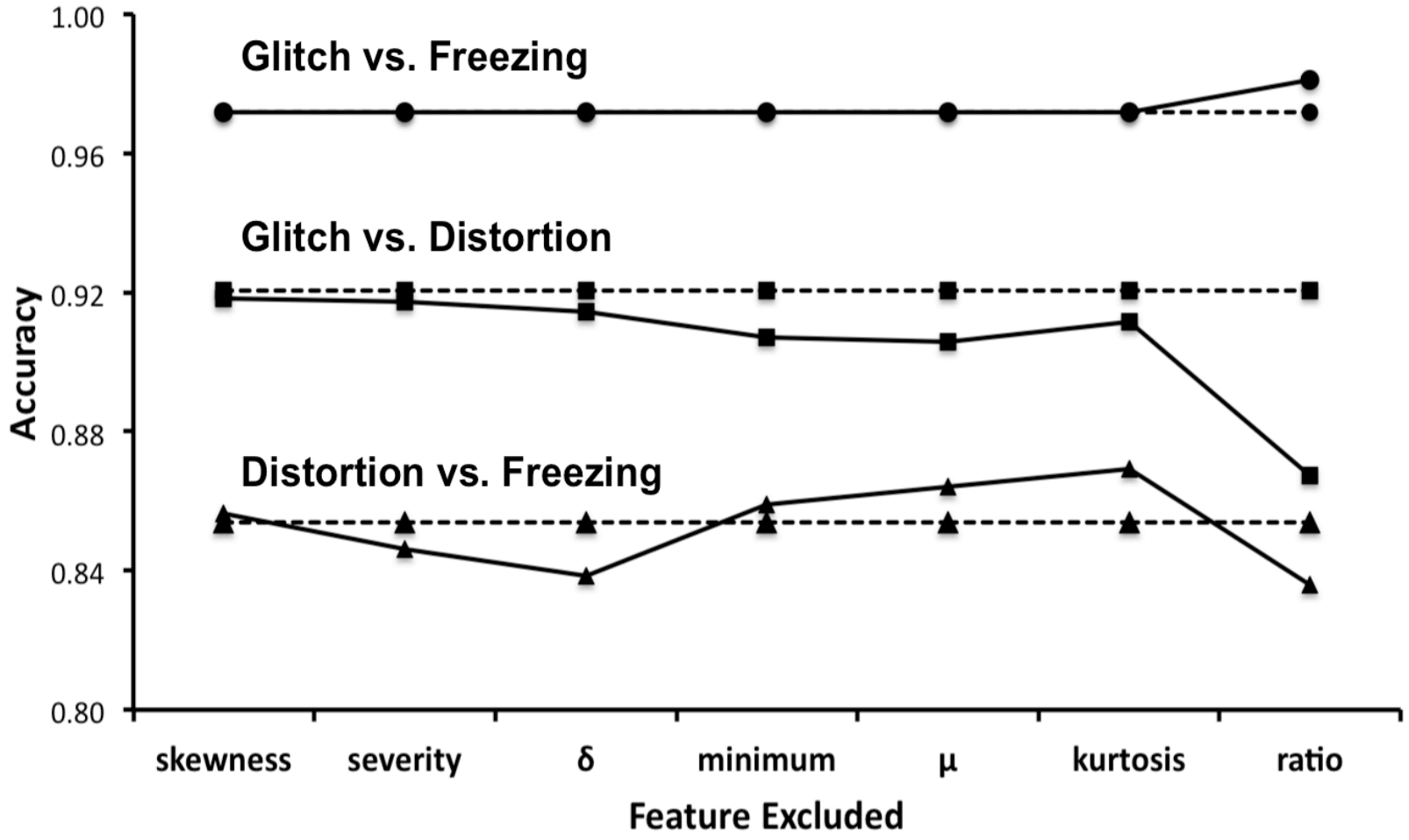
Background (2/2)

- **H.264/AVC**
  - Use spatial and temporal redundancy for compression
- **Measuring user experience**
  - Mean opinion score (MOS)
- **Machine learning (ML) techniques**
  - ML has been widely used in literature to establish correlation among metrics that are:
    - complex to mathematical model or statistically correlate
    - Containing many inter-dependent parameters (difficult to isolate and deduce from ground data)

Experiment Result – eSSIM Aggregator (3/3)

❖ Feature sensitivity

Dashed line: accuracy without feature excluded
Solid line: accuracy with feature excluded



❖ Preprocessing for eSSIM raw data

- Content filters (A. Kwon et al., 2012): luminance, frame complexity, scene change and motion
- Discontinuity filter
  - Frames dropped
  - Frames duplicated

$$eSSIM_{disc} = ssim(frame_b, frame_a) - 1,$$

- $eSSIM_{disc}$ has a range of [-1, 0]
- Points need to mention
  - The process of discontinuity filter is done at the server side
  - Scene change remedy: the first few frames following a scene change are not perceived (A. R. Reibman et al., 2007)

❖ Classification result of user MOS on Glitch and Freezing

Classified MOS

User MOS	6	7	8	9
6	0	0	1	0
7	0	1	4	1
8	0	0	13	0
9	0	1	3	2

(a) Glitch

16/26, 23/26

Classified MOS

User MOS	3	4	5	6	7
3	1	1	0	0	0
4	0	3	4	0	1
5	0	2	8	2	0
6	0	0	0	2	3
7	0	0	0	2	2

(b) Freezing

16/31, 30/31

User Experiment

- A single stimulus procedure
- A random playlist

eSSIM Aggregator (9/)

❖ Features extracted

- μ and δ: $\mu = \frac{\sum_1^n eSSIM_i}{n}$. $\delta = \sqrt{\frac{\sum_1^n eSSIM_i^2}{n} - \mu^2}$.
- *Minimum*: the minimum e*SSIM* value of an event
- *Defective ratio*: $ratio = \frac{N_{eSSIM<0.95}}{n}$.
- Severity of dropped and duplicated frames: $severity = \frac{N_{eSSIM\leq 0.0}}{n}$
- Skewness:
  - Measure of the asymmetric of the probability distribution of event data
  - [-1.0, 0.0, 0.1, 0.5, 0.8, 0.9, 0.95, 0.98, 1.0]
- Kurtosis: measure of whether the data are peaked or flat, relative to a normal distribution

❖ Preprocessing for features

- Middle-range normalization: [-1, 1]
- Mean-std normalization: mean = 0, std = 1

Objective metrics

❖ SSIM

- Full reference metric
- human visual perception is highly adapted for extracting structural information from a scene
- Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close

❖ PSNR

- computed by averaging the squared intensity differences of distorted and reference image pixels
- Inconsistent with human eye perception

❖ Statistical approach

- **A. Bhat et al., 2009**

$$MOS_p = 1 - k(MSE),$$

  - **Where MSE is the mean squared error, and k is derived from the spatial edge strength.**
  - **Do not consider distortion caused by varying network conditions**

- **O. Nemethova et al., 2006**

$$\widehat{MOS_{PSNR}}[n] = a \cdot PSNR[n] + b,$$

  - **Where n is frame index, a and b are derived from the relationship between PSNR and MOS**
  - **Frame-level metric, full-reference**

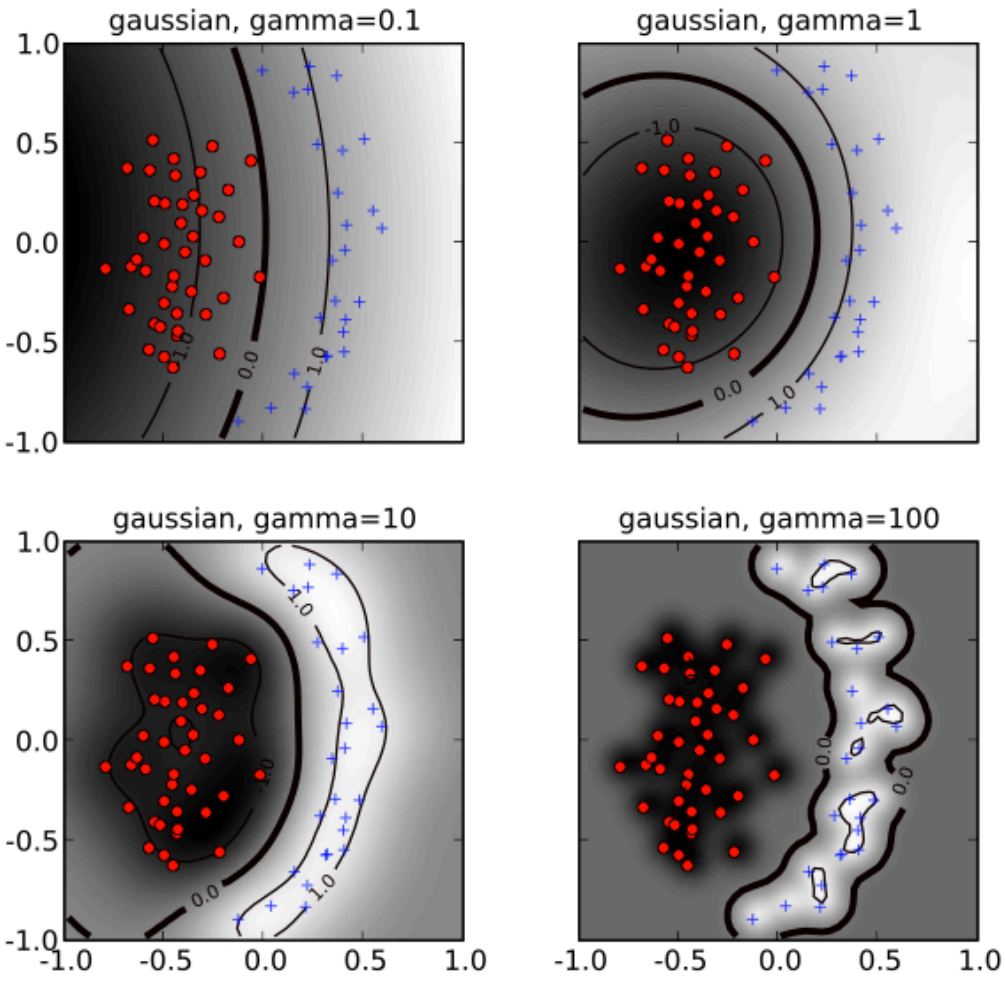
❖ Multiclass classification with SVM

- **Kernel selection**
  - **Radial basis function (RBF)**

$$k(\vec{x}, \vec{x_i}) = exp(-\gamma \|\vec{x} - \vec{x_i}\|^2),$$

- **Combination of binary SVM classifiers**
  - **One-versus-all: *M***
  - **One-versus-one: *M*(*M*-1)/2**

- **Parameters setting:**
  - ***C* and *γ***



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