

Quality Assessment of Blind Video Integrity

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Abstract –The Considerable progress has made toward developing still picture perceptual quality analyzers that do not require any reference picture and that are not trained on human opinion scores of distorted images. However, there do not yet exist any such type completely blind video quality assessment (VQA)models. Now we attempt to bridge this gap by developing a new completely blind video quality assessment model called the video intrinsic integrity and distortion evaluation oracle (VIIDEO). The new model does not need the use of any additional information other than the video being quality evaluated. video intrinsic integrity and distortion evaluation oracle embodies models of intrinsic statistical regularities that are observed in natural videos, which are used to quantify disturbances introduced due to distortions. An algorithm derived from the video intrinsic integrity and distortion evaluation oracle model is thereby able to predict the quality of distorted videos without any external knowledge about the pristine source, anticipated distortions, or human judgments of video quality. Even with such a paucity of information, we are able to show that the video intrinsic integrity and distortion evaluation oracle algorithm performs much better than the legacy full reference quality measure MSE on the LIVE completely blind video quality assessment database and delivers performance comparable with a leading human judgment trained blind blind video quality assessment model. We believe that the video intrinsic integrity and distortion evaluation oracle algorithm is a significant step toward making real-time monitoring of completely blind video quality possible. The software release of video intrinsic integrity and distortion evaluation oracle can be obtained online.

I. INTRODUCTION

The Digital videos 50% of both wire line and wireless data traffic is video data. Being able to monitor and control the perceptual quality of this traffic is a highly desirable Aim that could be enabled by the development of ‘completely blind’ video quality analyzers that could be inserted into video system or devices without any training or reference information. Towards this end, we have developed and explain here a ‘completely blind’ video integrity oracle dubbed video intrinsic integrity and distortion evaluation oracle. Like the ‘completely blind’ picture quality analyzer naturalness image quality Evaluator, the approach taken here is simultaneously ‘opinion-unaware’ and ‘distortion-unaware’. video intrinsic integrity and distortion evaluation oracle is even more penurious with respect to requiring exposure to other data: unlike naturalness image quality Evaluator, it is not trained on any data extracted from exemplar pristine videos, hence it is utterly ‘content unaware’ beyond using statistical models that can be shown to accurately characterize natural videos. While this may seem to be an extreme paucity of information, the use of perceptually relevant quantities yields results that are very promising. Indeed, the resulting algorithm predicts human judgments of video quality better than the long-standing full reference MSE on the LIVE Video quality analysis database.

This new no-reference video quality analysis approach is derived based on intrinsic statistical regularities that are observed in natural videos. Deviations from these regularities alter their visual impression. Quantifying measurements of regularity under a natural video statistic model makes it possible to develop a ‘quality analyzer’ that can predict the visual quality of a distorted video without external knowledge of any kind beyond the underlying model.

II. LITERATURE SURVEY

A no-reference video quality estimate method to monitor end user video quality. It is suitable for video applications transmitted over IP networks. Network IP conditions vary for individual users and ensure that end-user video quality is a big issue. To this end, you must monitor the video quality in the end user terminals. With the proposed method, video quality is estimated based on the number of macro blocks that contain errors that can not be hidden [1].

In [6] describe a database that contains the subjective assessment scores on 78 coded H.264 / AVC video sequences and corrupted by the simulation of incorrect network transmission. The

data was collected by 40 subjects on site of two academic institutions. Our goal is to provide a vast database to replicate results the field of video quality assessment. Paper [2] have developed a family of RR VQA algorithms that vary the amount of reference information needed to calculate the quality. These algorithms were based on statistical models for video in spatial and temporal domains and calculated differences in the amount of information between distorted references and videos to measure quality. While the algorithms with more video reference information we have come close to the performance of the full VQA algorithms, the algorithm of a single number has exceeded PSNR. We [5] first give a study that we run to evaluate the subjective quality of the videos. Our study included 10 uncompressed video clips from natural scenes and 150 Distorted videos (obtained from references) using four different types of distortions commonly encountered in applications. Each video was rated by 38 human subjects in one Single stimulation study with hidden reference hidden, where the subjects have noticed the quality of the video on a continuous quality scale. This study and its video database, presented here, which we call the Image and Video Engineering Laboratory (LIVE) Video quality database, complete the widely used LIVE image quality database for still images [1]. We evaluate the performance of the leading VQA target publicly available algorithms in the new LIVE video quality database using standardized measures. This [1] paper I have to proposed principles and methods of modern algorithms to automatically predict the quality of visual signals. Do the problem as well similar to the evaluation of the effectiveness of visual communication system, you can split the evaluation problem of the in understandable modeling problems. I [13] have to proposed metric to quantify the loss of frames based on the impact on perceived time quality. This metric looks especially to measure the temporal degradation of quality caused by both the loss of regular and irregular frames. Experimental results with subjective vision demonstrate high performance in predicting perceptual temporal quality. The [4] propose a blind IQA model that evaluates image quality without knowledge of the intended distortions or their human opinions. The quality of image is expressed as a simple distance metric between the the statistics of the model and the distorted image. The new model exceeds the FR IQA models and compete with the best NR IQA trained in human judgments of known distorted images. This model has great potential to be applied in environments. we [10] proposed estimation model explicitly considers the temporal error concealment algorithm adopted in the

decoder. In the evaluation of induced distortion, the effects of the absence of motion vectors and prediction residues are modelled in the decoding process. Here [7] evaluate different algorithm for image and video quality assessment (IQA / VQA) as far as the parrot effectiveness in foreshadows predicting visual quality. This is an unanalyzation of the correlation and analysis of the statistics. The general conclusion is that it is not sleepy at best because of the distortion of time. The database will be available on the VQA website and will be available for download from the DMOS website and will be available for download at the VQA website at any time in the field of validation of the video qualification. I [9] have to proposed video quality analysis system for on-demand video streaming monitoring, particularly on mobile / wireless networks. The algorithm adopts the noreference method and enables real-time video quality measurement at any point in the production and distribution chain of content using a specific video.

III. PROPOSED SYSTEM

we explain our ‘quality aware’ natural video statistics model in the space-time domain and describe the relevant temporal features that are derived from it and used to model inter sub band correlations over local and global time spans. The overall model, which we call video intrinsic integrity and distortion evaluation oracle, is the basis of a video intrinsic integrity and distortion evaluation oracle algorithm that predicts video quality in a manner that correlates quite well with human judgments of video quality.

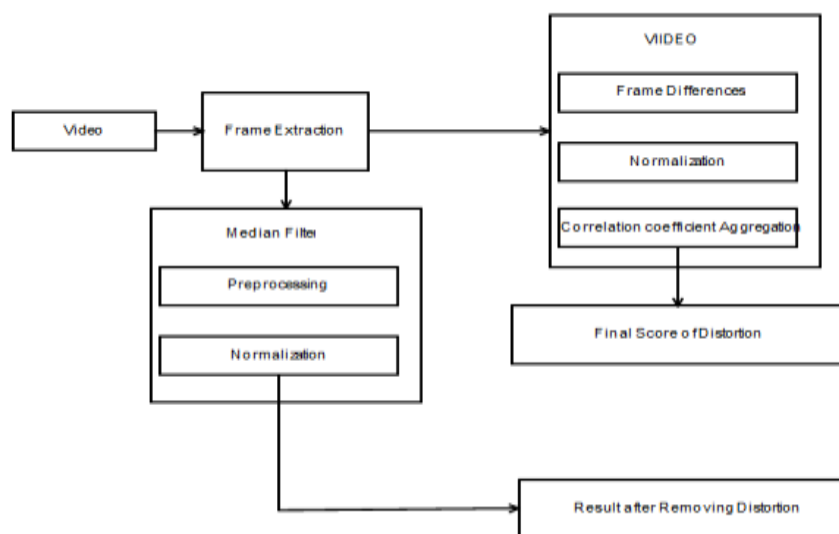


Fig 1. Architecture of Proposed System

We compare the performance of video intrinsic integrity and distortion evaluation oracle against existing state-of-the-art FR and NR video quality assessment approaches. Before we describe the statistical and perceptual underpinnings of the video intrinsic integrity and distortion evaluation oracle model in detail, we review relevant prior work in the area of video quality assessment. We described how the inter sub band correlations can be used to quantify the degree of distortion present in the video and hence to predict human judgments of video quality.

IV. Mathematical Formulae:-

Let S be a system having Input(I), Functions(F) and Output(O).

$$S=\{I,F,O\}$$

where, I is a video.

$$I=\{\text{Video}\}$$

O is the Score of Distortion, Remove Distortion.

$$O=\{\text{Score of Distortion, Remove Distortion}\}$$

F is the set of functions used for VIIDEO and median Filter.

$$F=\{F1, F2\}$$

where,

F1 is a function for VIIDEO.

F2 is a function for Median Filter.

F1 is a function for VIIDEO.

Frame Difference:

- Input: Video frame.
- Output: frame difference.

$$\Delta F^t = F^{2t+1} - F^{2t} \quad t \in \{0, 1, 2, \dots, \frac{T-1}{2}\}$$

where,

ΔF^t is the frame differences.

F^{2t+1} and F^{2t} is the consecutive frames of spatial dimensions $M \times N$.

T is the total number of frames.

t is the consecutive frame time sample.

Normalization:

- Input: Frame difference.
- Output: normalization.
- Functions:

$$\Delta F^t(i, j) = \frac{\Delta F^t(i, j) - \mu^t(i, j)}{\sigma^t(i, j) + C}$$

$$\mu^t(i, j) = \sum_{k=-k}^k \sum_{l=-L}^L W_k, l[\Delta F^t(i+k, j+l)]$$

$$\sigma^t(i, j) = \sqrt{\sum_{k=-k}^k \sum_{l=-L}^L W_k, l[\Delta F^t(i+k, j+l) - \mu^t(i, j)]^2}$$

where,

i is the $i \in \{1, 2, \dots, M\}$.

j is the $j \in \{1, 2, \dots, N\}$.

w k, l | k and l is the Gaussian weighting function, w k, l | $k=-k, \dots, k$ and

$l=-L, \dots, L$.

Correlation Coefficient Aggregation and Total Score:

- Input: normalization.
- Output: correlation coefficient aggregation and total score.
- Functions:

$$\Omega^{t+nk} = \sum_f \theta_f^{t+nk} \varphi_f \in \{1, 2, 3, \dots, 12\}$$

$$\varphi = \sum_{t+nk} \Omega^{t+nk}$$

where,

Ω^{t+1} is the empirical correlation coefficient.

Θ^{t+1} is the empirical correlation coefficient feature vector such

that $F \in \{1, 2, 12\}$

ψ is the total score.

$T + \eta k$ is the index.

F2 is a function for Median Filter.

- Input: Video frame.
- Output: Remove Distortion.
- Functions:
- $Y[m, n] = \text{median} \{X[i, j], (i, j) \in w\}$

where,

w is the neighbor defined by the user.

$[m, n]$ is the center parameter of image.

X, y is the axis.

i, j is the parameter.

V. ALGORITHM

Step1) T is the total number of frames extracted from Video.

Step2) We find frame differences between consecutive frames using ΔF .

$$\Delta F^t = f^{2t+1} - f^{2t} \quad \forall t \in \{0, 1, 2, \dots, \frac{(T-1)}{2}\}$$

Step3) The frame differences are operated on via processes of local mean removal and divisive contrast normalization.

$$\Delta F^t(i, j) = \frac{\Delta F^t(i, j) - \mu^t(i, j)}{\sigma^t(i, j) + C}$$

Step4) Here we used Asymmetric generalized Gaussian distribution for distinguishing two frames to find distortion between them based on moment matching approach.

Step5) For moment matching approach in two patches is calculated by using correlation coefficient aggregation as follow-

$$\Omega^{t+nk} = \sum_f \theta^t f + nk \quad \forall f \in \{1,2,3 \dots 12\}$$

Step5) The final score of distortion is obtain by using.

$$\psi = \sum_{f+nk} \Omega^{t+nk}$$

VI. RESULT ANALYSIS

In this model we have to upload all format video .it consist video AVI, MP3 ,3GP ,MOV ,MPG. For taking the input offline database is used in the system. That means any video which are stored in the memory are taken as an input. In this system the video which are stored in the drive are taken as an input. We also undertook a thorough creation of the VIIDEO model in terms of the correlation of the quality predictions it makes with human guess, and demonstrated that VIIDEO performs better.

Implemented Result is:-

Sr. no.	Video type	Vide o size	Fram es	MSE Result	VIID EO Result
1.	AVI	50mb	400	0.26	0.66
2.	Mp4	20mb	354	0.12	0.28
3.	3gp	8mb	210	0.15	0.27

TABLE 1

RESULTS FOR VIIDEO ALGORITHM WITH COMPARETIVE MSE ALGORITHM

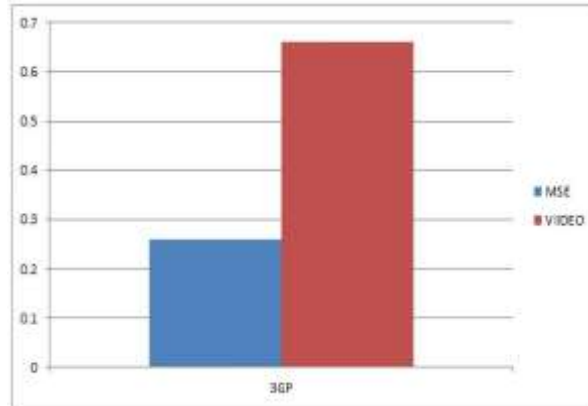


Fig2. Result Graph for 8 MB Video Size

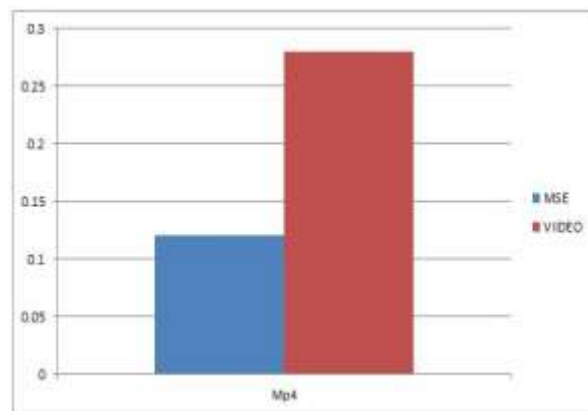


Fig3. Result Graph for 20 MB Video Size

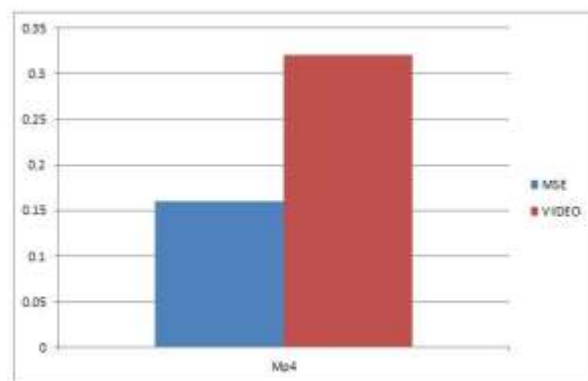


Fig4. Result Graph for 50 MB Video Size

Here we have to predict the quality of video. By using the VIIDEO algorithm approximate distortion is and as the base paper. Before applying the VIIDEO algorithm it will not and the approximate result and it also take more time for execution. The graph shows the result of VIIDEO Algorithm. Graph has x-axis as a video and y-axis as before applying VIIDEO algorithm and after applying VIIDEO algorithm. Fig. 3. Result Graph for 2 MB Video Size Fig. 4. Result Graph for 5 MB Video Size 1) Results: We give the video as an input to the system then by using VIIDEO algorithm the score of distortion is calculated. As the graph we take three video as an input one by one of different sizes such as 8 MB which has 3GP file format, 20 MB which MP4 file format and 50 MB which is also of AVI file format. In the result table we take four attributes as size of video, frame extraction, before VIIDEO and after VIIDEO. From the above graphical and tabular results, we get the score of distortion of the input video.

VII. CONCLUSION

We have proposed a ‘completely blind’ natural video statistics based quality assessment model - Video Intrinsic Integrity and Distortion Evaluation Oracle. It does not model any distortion specific information, but only models the statistical ‘naturalness’ (or lack thereof) of the video. We described how the inter sub band correlations can be used to quantify the degree of distortion present in the video and hence to predict human judgments of video quality. We also analyzed the time complexity of every step in the video intrinsic integrity and distortion evaluation oracle algorithm. The filtering and divisive normalization operations are the most computationally expensive steps, with complexity . However, since both of the steps involve point-based pixel wise computations, they are quite parallel in nature and can easily achieve linear scaling with the number of processors deployed to achieve the task. We also undertook a thorough evaluation of the video intrinsic integrity and distortion evaluation oracle model in terms of the correlation of the quality predictions it makes with human judgments, and demonstrated that video intrinsic integrity and distortion evaluation oracle performs better in this regard than the FR MSE metric. There is still scope for improvement by incorporating better models of motion for integration into blind video quality assessment algorithms. This may include more complete modeling of temporal filtering in the lateral geniculate nucleus (LGN) and motion processing in Areas MT/V5 and MST of extra striate cortex .The development of more detailed models of functional

processing in cortical area V2 remains a very energetic research area, with obvious positive implications for applied visual neuroscience problems of this kind.

REFERENCES

- [1] T. Yamada, Y. Miyamoto, and M. Serizawa, “No-reference video quality estimation based on error-concealment effectiveness,” in *Proc. Packet Video*, Nov. 2007.
- [2] F. de Simone, M. Naccari, M. Tagliasacchi, F. Dufaux, S. Tubaro, and T. Ebrahimi, “Subjective assessment of H.264/AVC video sequences transmitted over a noisy channel,” in *Proc. QoMEX*, Jul. 2009, pp. 204–209.
- [3] R. Soundararajan and A. C. Bovik, “Video quality assessment by reduced reference spatio-temporal entropic differencing,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 23, no. 4, pp. 684–694, Apr. 2012.
- [4] K. Seshadrinathan, R. Soundararajan, A. C. Bovik, and L. K. Cormack, “Study of subjective and objective quality assessment of video,” *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1427–1441, Jun. 2010.
- [5] C. Bovik, “Automatic prediction of perceptual image and video quality,” *Proc. IEEE*, vol. 101, no. 9, pp. 2008–2024, Sep. 2013.
- [6] K.-C. Yang, C. C. Guest, K. El-Maleh, and P. K. Das, “Perceptual temporal quality metric for compressed video,” *IEEE Trans. Multimedia*, vol. 9, no. 7, pp. 1528–1535, Nov. 2007.
- [7] A. Mittal, R. Soundararajan, and A. C. Bovik, “Making a ‘completely blind’ image quality analyzer,” *IEEE Signal Process. Lett.*, vol. 20, no. 3, pp. 209–212, Mar. 2012.
- [8] M. Naccari, M. Tagliasacchi, F. Pereira, and S. Tubaro, “No-reference modeling of the channel induced distortion at the decoder for H.264/AVC video coding,” in *Proc. 15th IEEE Int. Conf. Image Process.*, Oct. 2008.
- [9] A. K. Moorthy, L. K. Choi, A. C. Bovik, and G. de Veciana, “Video quality assessment on mobile devices: Subjective, behavioral and objective studies,” *IEEE J. Sel. Topics Signal Process.*, vol. 6, no. 6, pp. 652–671, Oct. 2012.
- [10] E. P. Ong *et al.*, “Video quality monitoring of streamed videos,” in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Apr. 2009.