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Video quality assessment based on Z-score

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ABSTRACT

Video quality is an important component in multi-media applications. Development of robust model for video quality assessment is an important challenge in this domain. Feature selection a crucial technique to identify the very important features in the give dataset. Z-score is a numerical measure which find the relationship to the average of the group of values.In this paper a novel feature selection model is introduced based on the Z-score value of the feature in the given dataset. Z-score is used as feature selection technique. Positive Z-score value features are selected to build the model.LIVE and CSIQ datasets are used to understand the performance of the model.The performance of the model is measured in terms of classification accuracy.

I. INTRODUCTION

Video quality is assessed based on the type of distortion. Subjective and Objective are two well-known assessment categories in VQA. These techniques provide high Quality of experience and Quality of service to the end users. The most easiest technique for evaluation is subjective assessment. It utilizes very high time and performed with the support ofend user[1].

Feature selection techniques find subsets of feature for high dimensional datasets. Generally, these methods are adopted in high data-intensive domains. This process is performed prior to the model development and decrease computational cost.Recently Z-score model is used in bankruptcy prediction. Model performance is evaluated with 31 European and 3 non-European countries firms. In this model we use Z-Score as feature selection technique. The model achieves 0.75 classification accuracy and shows 0.90 classification accuracy when use country specific estimation[2]. We believe that our study is an important contribution in VQA literature. Feature selection is a prior step to build the model and provides high quality output. Here, we used Z-score value as feature selector.

The remainder of the paper is organized as follows. Detailed literature review about VQA in section 2. Methodology is discussed in section 3. Experimental analysis is demonstrated in section 4. Concluding remarks are discussed in section 5.

II. LITERATURE REVIEW

Video quality is estimated by comparing perceived video quality degradation with the original video. Number of distortions presents in the video signal indicates video processing. Generally, Various distortions (noise, jitter, motion, blur etc.)during the acquisition effects the quality of the video. Therefore, it is necessary to remove these distortions from frames to preserve the quality of the video.It is noted that objective assessment techniques show high performance as compared to subjective assessment techniques. Objective assessment techniques are not depend upon human evaluation[1].

In literature, various feature selection techniques are proposed. Usually, wrapper and filter techniques are two popular types.In the filter technique, features are selected based on the performance classifier used. These are very low computational cost. In wrapper technique, a classifier is adopted to test eachfeature subset, it is also called as classifier-dependent .A novel estimation technique for no reference VQA is performed with the help of quantization in H.264/AVC videos without bitstream access,it can also be used for PSN ratio estimation. The experimental analysis are mapped from the MPEG-2 and H.264/AVC to a perceptual measure of video quality. Here, Support vector regression model is used as a classifier[3]. Similarly, another no reference model is proposed using sigmoid model by utilizing spatial-temporal features. Levenberg-Marquardt algorithm is used to find the weighted parameters[4].

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A study is carried to quantify just-noticeable-difference based VQA model using the satisfied user ratio (SUR) curve. The model achieves less than 0.05 mean absolute error[5]. Intensity variation analysis technique is adopted to VQA. High correlation between intensity metric-based VQAwith the Structural Similarity any category of video contents, resolutions and even bitrate setting. It shows high inter-frame intensity variation andhigh efficient as compared to SSIM in Variable bitrate transcoding system. Results indicate that the proposed model is 22 times better with respect to execution time (with compared to SSIM) [6].

III. METHODOLOGY

In this section, we discuss the methodology of our technique. The steps of the technique are shown as follow:

1) Calculate the Z-score for each feature of the given dataset. Here, Z-score is used for feature selection. Z-score of each sample is found using the following equation 1
i.eZ-Score <- (F - mean(F)) / standard deviation(F)------------------------------(1)

2) Find the average Z-score value of each feature
FS<- average (Z-Score)--(2)

3) Select the features which have positiveZ-Score value.

4) Build the model using the features which are identified in the Step 3

5) Estimate the Classification accuracy of the model as indicated in Fig. 1

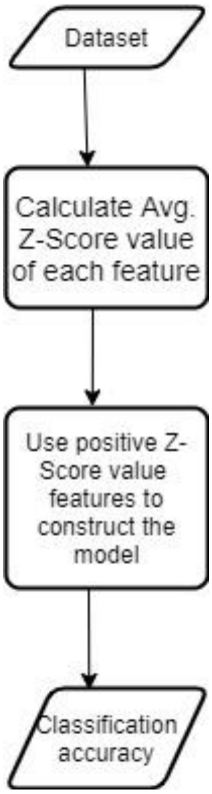

Fig.1 Steps of the proposed model

Experimental analysis

In this section, results of our experiments are discussed in detailed. We used a system with i5 processor, 1TB hard disc and 4GB RAM to conduct the experiments. The features of the dataset with the full form are mentioned in the Table 1.

Table 1: Features of the datasets used for the experiment

Sl.No	**Feature**	**Full-form**
1	FSIM	Feature Similarity Index Measure
2	CWSSIM	Complex Wavelet Structural Similarity Index Measure
3	GMSD	Gradient Magnitude Similarity Deviation
4	DSS	DCT Sub Band Similarity
5	QILV	Quality Index based on Local Variance
6	Corr2D	2D Correlation
7	NCC	Normalized Cross Correlation
8	PSNR	Peak Signal to Noise Ratio
9	MSE	M]ean Square Error
10	SSIM	Structural Similarity Index Measure
11	MSSIM	Multi Scale SSIM
12	3SSIM	Three Component SSIM
13	Delta	Difference of mean brightness of distorted image and mean original brightness
14	VQM DCT	DCT Based Video Quality Metric
15	MSAD	Mean Sum of Absolute Difference

Table 2 Classification accuracies of the proposed model

Classifiers	Live dataset		CSIQ dataset	
	Classification accuracy	Classification accuracy + Z-Score	Classification accuracy	Classification Accuracy+Z-Score
Decision tree(Fine)	35.2	38.1	22.2	22.7
Decision tree(Medium)	35.2	38.1	21.3	22.2
Decision tree(Coarse)	36.2	39.0	31.5	21.8
Kernel Naive Bayes	38.1	32.4	19.9	18.5
SVM(Linear)	43.8	47.6	27.3	29.6
SVM(Quadratic)	41.0	48.6	25.5	24.5
SVM(Cubic)	44.8	46.7	21.8	20.8
SVM(Fine Gaussian)	36.2	36.2	25.5	25.0
SVM(Medium Gaussian)	47.6	48.6	27.8	28.7
SVM(Coarse Gaussian)	31.4	35.2	29.2	29.6
Fine KNN	41.0	41.0	21.3	19.4
Medium KNN	32.4	41.0	22.7	20.4
Coarse KNN	31.4	31.4	27.8	27.3
Cosine KNN	34.3	34.3	22.7	21.8

Cubic KNN	35.2	42.9	22.2	21.3
Weighted KNN	41.9	41.9	23.1	24.5
Ensemble Boosted Trees	45.7	44.8	25.0	18.5
Ensemble - Bagged Trees	50.5	53.3	27.8	25.0
Ensemble Subspace Discriminant	40.0	44.8	28.7	31.0
Ensemble - Subspace KNN	35.2	39.0	20.8	18.1
Ensemble - RUSBoosted Trees	28.6	25.7	19.0	19.0

Table 2 indicates classification accuracies of the proposed model. Most of the models perform better as compared to traditional models for LIVE datasets. Medium KNN performs better among all other classifiers. It approximately shows 9% improvement as compared to its traditional Medium KNN algorithm for LIVE dataset. Similarly CUBIC KNN demonstrates nearly 7% improvement as compared to its counterpart for LIVE dataset. Only few classifiers show high performance as compared to traditional classifiers for CSIQ dataset.

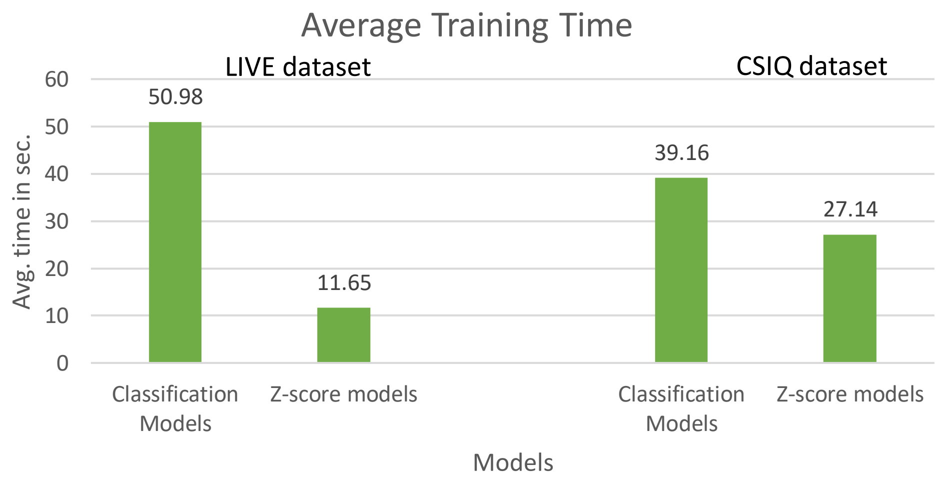

Fig.2 Average training time of the model

Fig. 2 shows an average training time (seconds) of the proposed model. Models with Z-score feature selection technique show approximately an improvement of 12% and 39% in terms of average training time for CSIQ and LIVE datasets respectively.

CONCLUSION

Video quality is necessary component in this internet era. Present study focuses on improvement classification accuracy for video quality assessment. Z-score is used as a feature selector technique. Model demonstrate superior than other traditional models. In future study, we would like to consider bio-inspired techniques to improve the performance of the model.

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