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Video quality assessment using optimization algorithms

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Abstract

Video quality assessment has seen more importance due to vast data entering the internet and multimedia communication network. This necessitates to predict the human observer's opinion for the video instead of perceptual quality estimation by human individuals. Two methods exist in video quality assessment based on involvement of human observer – subjective and objective methods. Subjective estimation of quality of video is based on rating of video quality perceived by human individuals and objective estimation is based on prediction of video quality using mathematical models which is well correlated with human observer quality scores. Objective video quality assessment research is gaining momentum because of amount of multimedia data entering into different media. Machine learning algorithms are making it easier to predict the quality of video using objective methods. Features of machine learning model are different individual visual metrics. In this paper, complete reference objective video quality assessment done with optimization algorithm applied for feature selection to predict video quality. In this paper, optimization algorithms-based feature selection is performed on LIVE and CSIQ Full Reference Video Database. Predominant features are selected to model video quality assessment. Regression is used to build the model. The results show the improvement in classification accuracy with the proposed method.

Keywords:Optimization, Feature selection, objective video quality metric, Regression, Machine learning models, Quality assessment

1- Introduction

Due to the advancement in the digital technologies, visual quality of digital media awareness has increased. Quality of the video is affected during the acquisition, transmission, compression and editing process of the video. Hence there is a need for video quality evaluation. To evaluate the visual quality qualitatively, human observers need to be shown both reference and test videos and asked to rate on a scale. Mean of these opinion scores of different individuals is the quality mark of the test video. But, with the voluminous data entering to internet and communication system, qualitative assessment poses a challenge. So, objective quality assessment is the way ahead. Objective quality of assessment aims to predict the quality of video without a human visual assessment. Objective video quality metrics rely on mathematical models to predict the quality of the video.

Video Quality Assessment (VQA) is a major research area which aims to design algorithms and to evaluate objective scores well correlated with subjective scores of the human visual system. Image qualityassessment metricsalso applied on frames of video for the video quality assessment with pooled temporal. Image and video quality analysis plays anvital role in the image and video processing applications like enhancement, compression, reconstruction etc.

Countless objective video quality metrics proposed in the past fewdecade. The challenge of video quality prediction lies in choosing right quality metric for the application. A single quality metric will not be sufficient to quantify the video. So, more than one quality metrics have to be preferred. Since, more and more objective video quality metrics are being prosed, it becomes difficult to include all the quality metrics in the model of prediction. So, best performing quality metrics have to be selected among the set of quality metrics considered. This process is also susceptible for errors since there are different categories of quality metrics like pixel based, information based, and similarity based etc. as well as single quality metric quantification may give false narrative of being a good quality metric than the set of quality indicators. In our work, we have tried to select best performing quality metrics for predictive model using optimization-based feature selection.

In our model, we have considered LIVE and CSIQ database. LIVE database is given by Laboratory of the Image and Video Engineering, University of 'Texas', Austin. CSIQ database is provided by 'Laboratory of Computational and Subjective Image Quality', Shizuoka University. These databases will help for the validation of objective video quality assessment algorithms.

CSIQ video database

The CSIQ video database[1] consists of twelve (12) high-quality reference videos and two hundred and sixteen (216) distorted videos from six (6) different types of distortion. SAMVIQ procedure was used to collect subjective ratings of quality during the experiment.

Videos which are in CSIQ database will be in YUV420 format having resolution with 832x480, duration of 10 seconds and has the frame rates of 24,25,30,50 and 60fps. For each reference video in database, distortion videos have six types of distortions at three levels. Compression and transmission-based distortion types are used to generate sample videos.

LIVE Database

The LIVE Video Database[2][3] consists of ten(10) reference videos in YUV format. Sample videos in LIVE database are created using 'MPEG2' compression, 'H.264' compression, simulated transmission of 'H.264' compressed bit streams through the error prone IP network and the wireless networks. For each of the reference video, 15 distorted test videos are created. Hence, it has 150 distorted videos. 38 human subjects have assessed distorted videos in single stimulus mode with hidden reference removal. The mean and difference of Mean Opinion Score (DMOS) obtained from subjective assessment.

Machine learning (ML) and deep learning (DL) are playing an important role in predictive video quality assessment. Machine learning will be used for building model ofquality video assessment for predicting the video quality quantitatively. In our approach, we have done regression based

2- Literature Survey

In this session, we discuss about the quality metrics considered for machine learning model and optimization methods used for feature selection.

a) Quality Metrics

Various quality measures have been proposed based on availability of reference image. There are three (3) types of metrics-based availability of reference image. They are (FR)Full Reference,(NR) No Referenceand (RR)Reduced Reference quality metrics. In our study, we have considered 16 FR video quality metrics.

SSIM (Structural Similarity Index Measure) [4] is a top-down approach for functionality of the overall (HVS)Human Visual System. Overall similarity of metric S (x, y) has 3 components: local luminance l(x, y), local contrast c(x, y)and structures(x,y) comparison between the original and the distorted images.

FSIM (Feature Similarity Index Measure) [5] points the features and measures the similarities between the two images. In this metric, (PC) Phase Congruency and (GM) Gradient Magnitude are taken for evaluation.

CWSSIM (Complex Wavelet Structural Similarity Index Measure) is syntactic similarity metric in the complex wavelet domain [6]

GMSD (Gradient Magnitude Similarity Deviation) isuses the gradient magnitude similarity of digital images to assess the image quality [7]

DSS (DCT Sub-band Similarity) DCT(Discrete Cosine transform) is linear transformation used for quality analysis [8]

SVD (Singular Value Decomposition)predicts the quality, based on the singular value decomposition. SVD will be applied on each 8x8 block of reference and test image. Differences of SVD's in reference and sample frames weighted by the edge-strength in every block, are used [9]

QILV (Quality Index based on Local Variance) is based on the consideration that variance distribution corresponds to high structural information. [10]

CORR2D (2D Correlation) is used to analyze how similar (or dissimilar) two spectral signals change. The correlation analysis describes in a quantitative manner how similar these two signals behave [11]

NCC (Normalized Cross Correlation) is the measure of finding similarity between two set of images. In image processing applications where the brightness of the image might vary due to lighting and exposure conditions, the images will be firstbring into normalized and used in finding the incidences of a pattern or an objects in the image [12].

PSNR(Peak Signal - Noise Ratio) [13] refer to the measure of logarithmic representation of MSE(Mean Square Error). It is used in earlier video quality research because of its simplicity and fast calculation. But, even additive noise will give higher PSNR suggesting of higher video quality. So, it is ignorant of spatial relationship and structure in the image.

MSE [14] points to the mean of squared error between the reference and sample frames of the video. It represents the simple pixel to pixel difference between reference and test frames of the video.

SSIM (Structural Similarity Index Measure) [4] has 3 comparisons namely luminance, contrast and structure and is one of the major metrics in the image and video quality assessment. Variants of SSIMs do exist.

Multi Scale – SSIM [15] is calculated on different scales of image. In our case, 5 scales are considered.

3SSIM – Three Component Structural Similarity [16] is using ‘edges’, ‘textures’ and ‘smooth regions’ of images and evaluates the metric value using weighted average of the SSIM metric for the said regions. Human visual system is the sensitive to texture and edge regions than smooth regions.

Delta - It represents the difference of mean brightness of distorted image and mean original brightness

DCT based VQM [17] - This Video Quality Metric (VQM) is based on Discrete Cosine Transform (DCT) for predicting human rank for the test video. It involves color transformation, DCT transformation of blocks 8x8, local contrast values are obtained from DCT coefficients, local contrast values are converted to noticeable difference and finally, weights are assigned for pooling of mean and maximum distortions.

Mean Sum of Absolute Differences (MSAD) – This metric depends only on difference of original and distorted, it is absolute of difference and will show real value of the difference between reference and test image. Value of zero indicates completely equivalent images.

b) Optimization Methods

Different optimization techniques and algorithms are proposed in the literature. Here, we list the optimization algorithms we have used for our implementation.

ASO (Atom search optimization) [18], is developed to address a diverse of optimization of the problems. this mathematically models and mimics the atomic motion model is its character, where itinteract through interaction forces resulting from the Lennard-Jones potential and constraint forces resulting from the bondlength potential.

GNDO (Generalized Normal Distribution Optimization) [19] introduces a generalization of the normal distribution also provide a comprehensive treatment of its mathematical properties.

EO (Equilibrium Optimizer) [20] in this, each particle is the solution with its concentration (position) acts as a search pool. The search pool randomly updates their concentration with respect to best-so-far solutions, namely equilibrium candidates, to finally reach to the equilibrium state i.e. optimal result. A well-defined “generation rate” term is proved to invigorate EO's ability in exploration, exploitation, and local minima avoidance.

MRFO (Manta Ray Foraging Optimization) [21] is outcome from intelligent behavior of the manta rays. This optimization mimics chain foraging, cyclone foraging and somersault foraging strategies of themanta rays for efficient optimization.

SMA (Slime Mould Algorithm Optimization) [22] is inspried on the oscillation mode of the slime mould in nature. Adaptive weights are used in this mathematical model. This optimization can mimic the process of positive and negative response of the propagation wave of slime mould to find short path.

ABC (Traditional Artificial Bee Colony Optimization) [23] is an optimization algorithm grounded on the intelligent geste of the honey freak mass

Traditional Ant Colony Optimization [24] is inspired from ant colony. It is a computational method based on probabilistic technique to find optimum path through graphs. Artificial ants represent methods inspired by the real ant’s behavior.

TPS (Traditional Particle Swarm Optimization) [25] is a computational method that will optimizes a problem by iteratively trying to improve the candidate problem solution with respect to a given measure of the quality.It solves a problem by having several seeker results, then dubbed patches, and moving these patches around in the hunt- space according to simple fine formulae over the particle's position and velocity.

c) Akaike Information Criterion (AIC)

For a set of data provided, estimation of prediction error and relative quality of statistical models can be accomplished with AIC. It is based on information theory. AIC can be used for model selection.

3- Methodology

Proposed methodology is shown in Figure 1. In our method, raw YUV420 videos of LIVE and CSIQ datasets are considered.

YUV method says, ‘Y’ refers to the brightness, or ‘luma’ value, and ‘UV’ refers to the color, or ‘chroma’ values. Since we haven’t considered the color in our quality analysis, we are accessing only the luminance component of the video. Y part of reference frame of reference videotape of dataset and Y part of distorted video (test videotape) frame are considered for objective videotapequality scores like SSIM, CWSSIM etc. We have considered first 100 frames of these datasets for our analysis. Hence, 100 quality scores for each quality metric are obtained. Pooling of these 100 quality scores will give a quality metric value for the particular dataset video.

3-1- Filter feature selection method

In this, statistical measures applied to assign a point to each feature. Ranking of the features by point is done and features are retained nor removed from the dataset. Many exemplifications of sludge point selection styles are chi-square test, information gain and correlation measure.

3-2- Wrapper feature selection method

Wrapper methods aim to search and select the set of features among all the features. Here, combinations of different features are made, evaluated, and compared to another combinations. Accuracy of the predictive model is used in assign a score to combination of the features and can be used to evaluate a combination of features.

The search process to find the subset of features may have best fit search, random hill climbing, heuristics like forward and backward passes or metaheuristics like optimization algorithms.

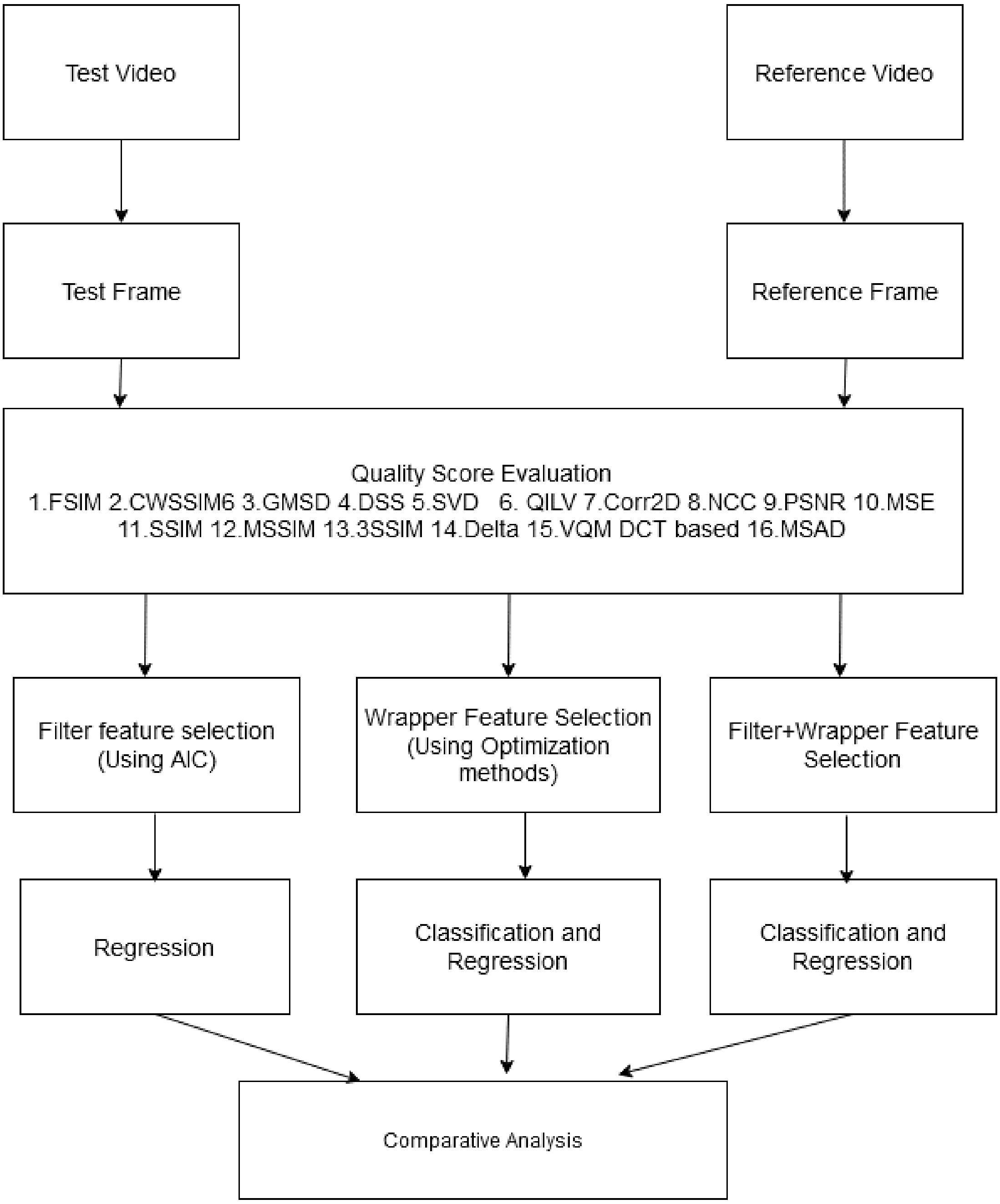

Figure 1: Methodology

3-3- Embedded method

In this method, feature selection process is embedded in the learning or model building phase. Regularization methods like LASSO, ridge regression, elastic net are examples for embedded methods.

While filter methods measure the relevance of the features, wrapper methods measure usefulness and give better performance. Embedded method lies in between these methods.

Selection of predominant feature from wrapper optimization methods

In this proposed method, we select the predominant features of a dataset based on repetition of same feature in different optimization methods. Among the 8 wrapper feature selection methods, if a feature is recurring in more than 3 optimization algorithm, we have considered that feature (quality metric) as predominant feature. This process is done for both LIVE and CSIQ database separately.

Algorithm for quality estimation model using predominant feature selection using wrapper optimization based feature selection methods

1. Find the Full Reference quality score between reference video frame and test(distorted) video frame

2. Pooling of quality scores of frames of video (Averaging as pooling strategy)
3. Repeat steps 1 and 2 for 16 image or video quality metrics considered in literature
4. Wrapper optimization-based feature selection with 8 optimization methods considered in literature
5. Listing of predominant features – metrics which appeared more than thrice in 8 different optimization methods.
6. Building the model of prediction using regression analysis with all the 16-quality metrics discussed in literature survey and finding RMSE.
7. Building the model of prediction with predominant features obtained in step 5, using regression analysis and finding RMSE
8. Comparative analysis of RMSE of step 6 and 7

Algorithm for quality estimation model with features selected from each of 5 category – Filtering method

1. Find the Full Reference quality score between reference video frame and test (distorted) video frame for LIVE and CSIQ databases.
2. Pooling of quality scores of frames of video (Averaging as pooling strategy) to obtain aindividual quality metric value for a sample video in the dataset.
3. Repeat steps 1 and 2 for 16 image/video quality metrics considered in literature
4. In our case, 16 metrics are divided into 5 categories as a) similarity-based metrics b) pixel-based metrics c) Block-wise evaluation metrics d) Correlation based metrics e) Deviation/Variance based metrics
5. Akaike Information Criterion is calculated for each of the quality metric(feature) in each category and metric with highest AIC is taken for next step.
6. For each of the feature selected/filtered in step 5, regression model is built and RMSE is evaluated for both LIVE and CSIQ databases separately.
7. Comparative analysis of RMSE

Algorithm for quality estimation model with features selected from each of 5 category using filtering and wrapper methods for further reduction in feature set – Filtering+Wrapper method

1. Quality metrics obtained from filtering using Akaike Information Criterion as filtering method are taken for this algorithm.
2. 8 Wrapper feature selection methods discussed in literature are applied for quality metrics considered in step 1
3. Features selected using 8 wrapper feature selection methods have consistency in feature selection and are used for building regression model
4. Comparative analysis of RMSE with different algorithms proposed is done.

4- Results and Discussion

In this part, we focus on the analysis of results. LIVE and CSIQ database are utilized to understand the performance analysis of video quality metrics. LIVE database videos have wide variety of content. Table 1 shows optimization algorithms used for feature selection for LIVE and CSIQ full reference video database along with the accuracy for each of the optimization algorithm. We have done the implementation using Matlab 2020a. Regression leaner is used for the evaluation of RMSE.

Quality metrics (features)

1. FSIM 2. CWSSIM6 3. GMSD 4. DSS 5. SVD 6. QILV 7. Corr2D 8.NCC 9. PSNR 10.MSE 11. SSIM 12. MSSIM 13.3SSIM 14. Delta 15.VQM DCT based 16. MSAD

Table 1 shows the features selected using wrapper feature selection methods. Table 2 shows features selected using filter method and wrapper method.Table #3 shows theRMSE (Root Mean Square Error) result of regression model built using predominant features obtained so far. First two columns show results of regression RMSE with predominant feature selection whereas third and fourth columns show the regression results for without feature selection. It can be noted from Table 2 that, instead of all the 16 quality metrics used for training, only predominant features can be considered and higher accuracy of predictability could be achieved. Table 3 enlists regression RMSE with and without predominant feature selection through feature selection algorithms. Table 4 provides the results related to regression RMSE with AICs as filter feature selection criterion. This evaluation has considered filter feature selection criterion and without wrapper feature selection. Table 5

TABLE 1

Feature selection from 16 features using wrapper feature selection methods

Sl. NO	Optimization Algorithm	Database	Features Selected (Among 16 features)	Accuracy
1	Atom Search Optimization (ASO)	LIVE	8,7	47.61
		CSIQ	6 7 8 9 10 11	34.88
2	Generalized Normal Distribution Optimization (GNDO)	LIVE	2 3 4 6 13	42.85
		CSIQ	9 10 11 16	37.20
3	Equilibrium Optimizer (EQ)	LIVE	1 3 12	61.90
		CSIQ	1 9 10	37.20
4	Manta Ray Foraging Optimization (MRFO)	LIVE	6 7 12 16	61.90
		CSIQ	9 10 11	37.20
5	Slime Mould Algorithm Optimization (SMA)	LIVE	6	42.85
		CSIQ	7 9 10	37.20
6	Traditional Artificial Bee Colony Optimization (ABC)	LIVE	1 3 6 7 8 12 14	**66.66**
		CSIQ	9 10 15	37.20
7	Traditional Ant Colony Optimization	LIVE	8 7	47.62
		CSIQ	9 7 10	37.21
8	Traditional Particle Swarm Optimization	LIVE	4 7 11 12 14	42.85
		CSIQ	1 9 10	37.21

Optimization based feature selection process is done for both LIVE and CSIQ database separately. We found that for LIVE database, GMSD, QILV, Corr2D, NCC, MSSIM appeared 3 or more times in 8 optimization algorithms for feature selection. For CSIQ database, Corr2D, PSNR, SSIM and MSSIM appeared 3 or more times in feature selection using optimization algorithms. So, we can consider these features as predominant features in respective databases. These predominant features are used for building regression model for prediction of video quality

Akaike Information Criterion (AIC) is used as filtering mechanism to select features for both LIVE and CSIQ databases.

Quality metrics for CSIQ database and indices used – using filtering method with AIC

1'. CWSSIM 2'. Delta 3'. DSS 4'. CORR2D 5'. GMSD

Quality metrics for LIVE database and indices used – using filtering method with AIC

1'. MSSIM 2'.PSNR 3'. VQM 4'. Corr2D 5'.QILV

Table 2 Features selected using BOTH filtering and wrapper feature selection methods using different optimization methods for LIVE and CSIQ databases

Sl. NO	Optimization Algorithm	Database	Features Selected (Among 5 category)	Accuracy %
1	Atom Search Optimization (ASO)	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88
2	Generalized Normal Distribution Optimization (GNDO)	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88
3	Equilibrium Optimizer (EQ)	LIVE	1’	42.86
		CSIQ	2’ 3’ 4’	34.88
4	Manta Ray Foraging Optimization (MRFO)	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88
5	Slime Mould Algorithm Optimization (SMA)	LIVE	1’ 2’ 4’	52.38
		CSIQ	1’ 4’	30.23
6	Traditional Artificial Bee Colony Optimization (ABC)	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88
7	Traditional Ant Colony Optimization	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88
8	Traditional Particle Swarm Optimization	LIVE	1’ 2’ 4’	52.38
		CSIQ	2’ 3’ 4’	34.88

Table 2 and 3 show the classification accuracies for wrapper feature selection methods and filter+wrapper feature selection methods. It can be noted that with hybrid feature selection using filter and wrapper methods, features from 5 groups may be selected. Consistency is achieved in classification accuracy with this hybrid method. This method worked well for LIVE database and among 8 optimization algorithms used for feature selection, classification accuracy improved in 5 algorithms.

TABLE 3

Regression RMSE with and without predominant feature selection through wrapper feature selection algorithms (Without filter feature selection)

Regression learner	**LIVE**	**CSIQ**	**LIVE w/o**	**CSIQ w/o**
Linear regression - linear	0.16	1.43	0.79	1.38
Linear regression - Interactions linear	0.21	1.50	160.61	59.42
Linear regression - Robust Linear	0.16	1.44	0.83	1.38
Stepwise linear regression	0.16	1.46	0.81	1.45
Fine tree	0.18	1.60	0.90	1.65
Medium tree	0.20	1.55	0.98	1.46
Coarse tree	0.23	1.46	1.08	1.42
Linear SVM	0.16	1.44	0.85	1.39
Quadratic SVM	0.18	1.53	1.50	2.44
Cubic SVM	0.22	1.76	16.53	5.33
Fine Gaussian SVM	0.24	1.42	0.94	1.43
Medium Gaussian SVM	0.13	1.41	0.74	1.37
Coarse Gaussian SVM	0.16	1.44	0.84	1.39
Ensemble Boosted trees	0.20	1.49	0.77	1.41
Ensemble Bagged Trees	0.19	1.45	0.96	1.39
Gaussian Process RegressionMatern 5/2 GPR	0.13	1.43	0.71	1.37
Gaussian Process Regression - Exponential GPR	0.13	1.43	0.71	1.37
Gaussian Process Regression - Rational Quadratic GPR	0.13	1.43	0.72	1.37

Table 4
Regression RMSE with AIC as filter feature selection criterion (Without wrapper feature selection)

Regression learner	**LIVE AICC**	**CSIQ AICC**	**LIVE w/o**	**CSIQ w/o**
Linear regression - linear	0.94	1.39	0.79	1.38
Linear regression - Interactions linear	1.16	1.44	160.61	59.42
Linear regression - Robust Linear	1.38	1.39	0.83	1.38
Stepwise linear regression	0.75	1.39	0.81	1.45
Fine tree	0.89	1.68	0.90	1.65
Medium tree	0.94	1.47	0.98	1.46
Coarse tree	1.02	1.39	1.08	1.42
Linear SVM	1.04	1.42	0.85	1.39
Quadratic SVM	0.79	1.52	1.51	2.44
Cubic SVM	47.04	5.44	16.53	5.34
Fine Gaussian SVM	0.90	1.48	0.94	1.43
Medium Gaussian SVM	0.73	1.43	0.74	1.37
Coarse Gaussian SVM	0.83	1.41	0.84	1.39
Ensemble Boosted trees	0.78	1.46	0.77	1.41
Ensemble Bagged Trees	0.91	1.45	0.96	1.39
Gaussian Process RegressionMatern 5/2 GPR	0.72	1.39	0.71	1.37
Gaussian Process Regression - Exponential GPR	0.71	1.40	0.71	1.37
Gaussian Process Regression - Rational Quadratic GPR	0.72	1.39	0.72	1.37

TABLE 5

Regression RMSE with BOTH filter feature selection with AIC and wrapper feature selection using predominant features

Regression learner	**LIVE AICC +Pred. Features**	**CSIQ AICC +Pred. Features**	**LIVE w/o**	**CSIQ w/o**
Linear regression - linear	1.10	1.40	0.79	1.38
Linear regression - Interactions linear	0.88	1.41	160.61	59.42
Linear regression -Robust Linear	1.37	1.40	0.83	1.38
Stepwise linear regression	0.78	1.41	0.81	1.45
Fine tree	0.91	1.63	0.90	1.65
Medium tree	0.90	1.46	0.98	1.46
Coarse tree	0.98	1.41	1.08	1.42
Linear SVM	1.16	1.41	0.85	1.39
Quadratic SVM	1.18	1.43	1.51	2.45
Cubic SVM	18.61	2.48	16.53	5.34
Fine Gaussian SVM	0.82	1.45	0.94	1.43
Medium Gaussian SVM	0.76	1.42	0.74	1.38
Coarse Gaussian SVM	0.81	1.42	0.84	1.39
Ensemble Boosted trees	0.81	1.47	0.77	1.41

Ensemble Bagged Trees	0.89	1.50	0.96	1.39
Gaussian Process RegressionMatern 5/2 GPR	0.76	1.40	0.71	1.37
Gaussian Process Regression - Exponential GPR	0.73	1.41	0.71	1.37
Gaussian Process Regression - Rational Quadratic GPR	0.74	1.40	0.72	1.37

Conclusion

The paper says, the proposed optimization methods are based predominant feature selection of predictive video quality analysis. Wrapper feature selection based on optimization is used to select the quality metrics. Eight optimization algorithms are used to select features. The metrics which appeared more than thrice have been taken as predominant features of the particular database. We found that for LIVE database, GMSD, QILV, Corr2D, NCC and MSSIM are predominant features. For CSIQ database, Corr2D, PSNR, SSIM, MSSIM are found to be predominant features. We can conclude that we can build hybrid metric using these features. RMSE for with predominantselection feature is less than the 1 without selectionfeature. In our case, we have used wrapper optimization methods-based feature selection. We can improve the feature selection using both filter-based approach and wrapper feature selection approach if we have large subset of features. We have obtained consistent features from 5 categories with usage of both filter feature selection process using AIC as well as wrapper feature selection process. Hence, hybrid feature selection using filter and wrapper methods help in obtaining consistent and best performing features for building the model.

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