A NOVEL APPROACH FOR NO-REFERENCE QUALITY ASSESSMENT OF JPEG2000 IMAGES AND H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM

A THESIS

submitted by

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(101PG05001)

for the award of the degree

of

DOCTOR OF PHILOSOPHY

DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING
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OCTOBER 2016

Dedicated

to

My family and friends!

DECLARATION

I hereby declare that the work described in this thesis, entitled "**A NOVEL APPROACH FOR NO-REFERENCE QUALITY ASSESSMENT OF JPEG2000 IMAGES AND H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM**" which is being submitted by me for the award of **Doctor of Philosophy** in the Dept. of Electronics and Communication Engineering to Vignan's Foundation for Science, Technology and Research University, Vadlamudi, Guntur, is the result of investigations carried out by me under the Guidance of Dr. D.Venkata Rao, Guide, Principal, Narasaraopeta Institute of Technology, Narasaraopeta and Dr. N.Usha Rani, Co-Guide, Professor & Head of the Department, Vignan's Foundation for Science, Technology and Research University, Vadlamudi, Guntur.

The work is original and has not been submitted for any Degree/Diploma of this or any other university.

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THESIS CERTIFICATE

This is to certify that the thesis entitled **A NOVEL APPROACH FOR NO-REFERENCE QUALITY ASSESSMENT OF JPEG2000 IMAGES AND H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM** submitted by **SUBRAHMANYAM.CH** to the Vignan's Foundation for Science, Technology and Research University, Vadlamudi, Guntur for the award of the degree of **Doctor of Philosophy** is a bonafide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

I am lucky and privileged that I could get **Dr.D.Venkata Rao,** Principal, Narasaraopeta Institute of Technology, Narasaraopeta as my Ph.D Research Guide. It has been a pleasure and great learning experience working with him. I am very much thankful to him for his mature and balanced guidance style that permitted me to explore and experiment with my ideas and convictions during the research period, which helped me to gain confidence to do independent research.

I take immense pleasure to express my deep sense of gratitude to my Ph.D Research Co-Guide **Dr.N.Usha Rani,** Prof. of ECE & HOD, VFSTR University, Guntur for her meticulous supervision, unfailing support and for constant source of encouragement and inspiration throughout my research work.

I express my sincere thanks to **Dr.C.Thangaraj,** Vice Chancellor, **Dr.A.Srinivasulu,** Dean – R&D, VFSTRU, **Dr.B.Seetha Ramanjaneyulu,** Dean – Academics for offering their advices and suggestions for carrying out the research work. I am thankful to **Dr.P.Subbaraj**, **Dr.N.Ramaraj** and **Dr.D.Venkateswarlu** for serving in my doctoral committee panel and for offering their advices and suggestions during the research monitoring meetings. I am also thankful to **Dr.M.S.S.Rukmini**, and **Dr.V.Ranganathan** for offering their advices.

I thank **Smt. B.Udaya Lakshmi,** IAS, Commissioner of Technical Education, Government of Andhra Pradesh for giving the permission to do research work in VFSTR University. I sincerely thank **Dr. A. C. Bovik**, Director of Laboratory for Image & Video Engineering (LIVE), University of Texas, Austin and his team **Anush Murthy, Anish Mittal, Deepti Ghadiyaram** for their valuable suggestions, encouragement and also providing the software and database used for this work.

I would also thank my parents, parents-in-law, my wife and son for their patience, love, support and understanding. Finally I would like to thank all those who have involved directly or indirectly in the completion of my research.

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ABSTRACT

A NOVEL APPROACH FOR NO-REFERENCE QUALITY ASSESSMENT OF JPEG2000 IMAGES AND H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM

KEYWORDS: No Reference, Image Quality Assessment, Video Quality Assessment, Human Visual System, JPEG2000, H.264, threshold, human judgements.

The quality assessment is one of the most intriguing challenges in the media environment during the last decade in many applications. The images and videos are captured using different devices like handycams, cameras, and mobile phones. The captured image and video data is stored in memory and transmitted from one device to other device or accessed from the web. The important task for any image and video quality metric is to assess the quality of the image/video on par with human visual system in subjective judgement.

The quality assessment algorithms are classified in accordance with the information available about the original images and videos. The quality assessment can be done by using Full Reference (FR), Reduced Reference (RR) and No Reference (NR) methods. The entire original image/video is available as a reference in FR method. FR methods are based on comparing distorted image/video with the original image/video. RR method is not required to give access to the original image/video but only to provide representative features about texture or suitable characteristics of the original image/video. In NR method, image/video quality assessment is done without considering the original image/video. In recent years, there has been increasing interest in the development of NR methods due to the widespread use of multimedia services in the context of wireless communications and telecommunications systems.

In the last few decades, the quality assessment of the images and videos are based on the known characteristics of the Human Visual System (HVS). A new paradigm for image and video quality assessment based on the HVS is highly adopted for distorted images and videos. No Reference image and video quality assessment algorithms are developed by using machine learning techniques along with human judgements for quality. The approach of quality assessment based on product of pairs and their localized distortions of adjacent pixels with the difference of one. If that concept is

considered, only four orientations are covered in the BRISQUE (Blind or Referenceless Image Spatial Quality Evaluation) algorithm, which is not suitable for the overall image metric calculation. This is the drawback of BRISQUE algorithm. To overcome this drawback, the proposed algorithm considers six orientations with difference in adjacent pixel values.

The proposed algorithm is No Reference Distortion Patch features Image Quality Assessment (NRDPF-IQA) for images and No Reference Distortion Patch Features Video Quality Assessment (NRDPF-VQA) for videos. The proposed algorithm estimates the quality of image/video based on the distortion patch features of the image/video and patch size of the image/video. The NRDPF-IQA is developed based on Human Visual System to follow the visibility threshold of the images and to obtain the overall image quality scores.

In the Human Visual System models, two fundamental tasks are performed. One is predicting the significance of the image/video. Another one is to predict the visual significance of images including mechanisms to simulate. HVS based analytics are usually developed with regards to either a bottom-up or a top-down view point. The features of the different HVS elements are developed by computational methods and incorporated into a natural design of recognizably good quality. The quality of image/video is judged by stereo operators in subjective scales for contrast, sharpness, granularity, interpretability and overall quality.

The functions for forecasting the perceived picture quality are extracted by considering Human Visual System factors such as contrast, sharpness and luminance. Picture quality assessment involves calculating the functional relationship between HVS functions and subjective test scores. Here, the problem of quality evaluation is modified to a classification problem and fixed using No-reference distortion patch features image quality assessment criteria. The features are calculated from locally normalized luminance of pixels and differences of locally normalized luminances under a spatial domain. In spatial domain, no transformation technique is required.

The proposed algorithm estimates quality based on features of the image. The no reference distortion patch features IQA model utilizes a spatial domain approach based on L-moments. NRDPF-IQA is statistically better than the Full-Reference PSNR, SSIM, MS-SSIM methods and other No Reference methods. NRDPF-IQA has very low computational complexity compared with other models, making it well suited for real time applications. NRDPF-IQA features may be used for distortion-identification as well. Results show that NRDPF-IQA model perform better than the state-of-the-art methods.

The NR quality metric for JPEG2000 images and H.264 videos are trained and tested. The metric focuses on distortion patch features of the image, given their predominance in JPEG2000 compressed images, and consider blur indirectly. The quality performance of the work has been considerably improved by NRDPF-IQA/VQA method. Each image/video is assessed by 36 human subjects and the Difference Mean Opinion Scores (DMOS) is recorded along with the Spearmen Rank Order Correlation Coefficients (SROCC) and Pearson (Linear) Correlation Coefficients (LCC) values. The evaluation is done by the publicly-available IQA/VQA databases.

Finally, the quality assessment of JPEG2000 images and H.264 videos are analyzed based on Human Visual System using NRDPF-IQA/VQA algorithm. Owing to the many approaches to No Reference Distortion Patch Features Image/Video Quality Assessment (NRDPF-IQA/VQA) is being implemented on using LIVE database and Vignan University database of distorted images/videos. Based on these findings, it is revealed that the distortion patch features of no reference image/video have an impact on the overall quality assessment.

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ABBREVIATIONS

ACR	Absolute Classification Ranking
AGGD	Asymmetric General Gaussian Distribution
BER	Bit Error Rate
BLIINDS-II	BLinds Image Integrity Notator using DCT Statistics - II
BRISQUE	Blind/Referenceless Image Spatial Quality Evaluator
CBIQ	Visual Codebook based metric Image Quality
CSF	Contrast Sensitivity Function
CSIQ	Computational Perception and Image Quality
DCR	Degradation Classification Ranking
DCT	Discrete Cosine Transform
DIIVINE	Distortion Identification-based Image Integrity and Verity Evaluation
DMOS	Differential Mean Opinion Score
DVQ	Digital Video Quality
EPFL-PoliMi video database	Ecole Polytechnique Federale de Lausanne and the Politecnico di Milano video database
FR	Full Reference
FRTV	Full Reference Television
FR VQA	Full Reference Video Quality Assessment
GGD	Generalized Gaussian Distribution
GSMs	Gaussian Scale Mixtures
H.264/AVC	MPEG-4 Part 10, Advanced Video Coding (MPEG-4 AVC)
HDTV	High-Definition Television
HVS	Human Visual System
IP	Internet Protocol
IPTV	IP address TV
IQM	Image Quality Metric
IRCCyN/IVC database	Institute of Research in Communication and CyberNet/ Images and Video Communications database
ITU	International Telecom Union
ITU-R	Radio communications industry of the ITU
ITU-T	Telecoms industry of the ITU
JND	Just-Noticeable Differences
JPEG2000	Joint Photographic Experts Group 2000 standard

LBIQ	Learning a Blind measure of perceptual Image Quality
LCC	Pearson’s (Linear) Correlation Coefficient
Lib SVM	Library Support Vector Machine
LIVE database	Laboratory for Image & Video Engineering database
MAD	Most Apparent Distortion
MAE	Mean Absolute Error
MICT database	Media Information and Communication Technology Laboratory database
MOS	Mean Opinion Score
MOVIE	Motion-based Video Integrity Evaluation index
MPEG	Moving Picture Experts Group
MPEG-2	H.262 as defined by the ITU
MSCN	Mean Subtracted Contrast Normalized
MSE	Mean Squared Error
MSSIM	Multiscale Structural Similarity index
NR	No Reference
NR-IQA	No Reference Image Quality Assessment
NR-VQA	No Reference Video Quality Assessment
NRDPF-IQA	No Reference Distortion Patch Features Image Quality Assessment
NRDPF-VQA	No Reference Distortion Patch Features Video Quality Assessment
NSS	Natural Scene Statistics
NVS	Natural Video Statistics
NYU database	New York University database
PDM	Perceptual Distortion Metric
PEAQ	Perceptual Evaluation of Audio Quality
PESQ	Perceptual Evaluation of Speech Quality
PSNR	Peak Signal-to-Noise Ratio
QA	Quality Assessment
QAF	Quality Assessment Framework
QoE	Quality of Experience
QoS	Quality of Service
QQ Plot	Quantile Quantile Plot
RBF	Radial Basis Function kernel
ROI	Region of Interest

RR	Reduced Reference
RRED	Reduced Reference Spatio Temporal Entropic Differencing
SNR	Signal-to-Noise Ratio
SROCC	Spearman’s Rank Ordered Correlation Coefficient
SSIM	Structural Similarity index
STMAD	Spatio Temporal Most Apparent Distortion
SVM	Support Vector Machine
SVR	Support Vector Machine Regressor
TetraVQM	Temporal Trajectory Aware Video Quality Measure
TID	Tampere Image Database
VA	Visual Attention
VDP	Visible Differences Predictor
VIDEO BLIINDS	VIDEO BLinds Image Integrity Notator using DCT Statistics
VIF	Visual Information Fidelity
VIFC	Visual Information Fidelity Criterion
VL bit rate	Visually Lossless bit rate
VoD	Video on Demand
VQEG	Video Quality Expert Group
VQM	Video Quality Metric
VSNR	Visible Signal-to-Noise Ratio
VU database	Vignan University database
Wi-Fi	Wireless Fidelity

NOTATIONS

English Symbols

C	constant
C_h	coherence
CD	Combine Diagonal
f	Asymmetric probability density function
f_γ	Exponent that differs over a little range across image
H	Horizontal
HV	Horizontal Vertical
I(i,j)	Coefficients corresponding to spatial place i,j
$I_1(x,y)$	Image 1 on pixel by pixel bases
$I_2(x,y)$	Image 2 on pixel by pixel bases
J	Image sub groups
K	Constant or continuous
K_0	Bessel function
M	Image height
$M_x(i,j)$	Horizontal moment vector
$M_y(i,j)$	Vertical moment vector
MD	Main Diagonal
N	Image width
N_s	samples
P	pixel
SD	Secondary Diagonal
T	Threshold
V	Vertical
X	Horizontal image dimension
$X_{(i)}$	L-moments of samples
Y	Vertical image dimension

Greek Symbols

$\mu(i,j)$	mean
γ	Form parameter
η	Mean of submission
σ	variance
σ^2	covariance
$\boldsymbol{\rho}$	Correlation coefficient of adjacent coefficient
λ	Eigen values
Γ	Ordinary gamma function

Chapter-1

INTRODUCTION

1. INTRODUCTION

1.1. General

The individual Human Visual System (HVS) is often regarded to be the most popular of our feeling body parts to acquire information from the outside globe (C.J.Van et al., 1996). Without our vision human would live in night and would not be able to appreciate the elegance around the globe around us. During all stages of individual progress our sight were tailored to monitoring a habitat. This has modified only in recent years with the implementation of many visible technological innovations such as TV, theatre, computer displays, and most lately mobile phones. These popular technological innovations now highly impact our daily work and personal life and many people, especially of young people, have complications visualizing a time before these technological innovations were available. Hence, it is getting more and more used to not just looking at the habitat around us, but rather at synthetic copies, with regards to electronic pictures and video clips. This is especially allowed through latest developments in interaction technological innovation, such as the Internet and 4^{th} generation cellular stereo systems, which allow submission and discussion of visible content in a popular way.

The range of picture and movie handling techniques that accomplish visible copies of the actual life is broad and includes picture and movie acquisition, enhancement, and interaction techniques (chin et al., 1999). These techniques are usually designed based on a compromise between technical resources and the visible quality outcome. Since it is accustomed to outstanding quality natural scene statistics, it is one-sided to expect also a certain degree of quality from its digital visible representations. However, the quality is often reduced due to many impacting factors, including, capture, transmitting, and display of the picture or movie. These processes potentially introduce disturbances into the visible material resulting in a reduction of perceived quality. This is often due to the naturalness of the visible scene being affected, meaning, that components are changed or presented that are not observed when looking at natural scene statistics.

The deterioration in quality depends extremely on the type and severeness presented by the different handling actions. Visual materials are thus particularly interested in measuring the quality loss presented in any of the handling actions involved, which is important for ensuring a certain level of visible experience to the viewer. This is especially crucial for Wi-Fi network suppliers (R.W.Heath et al., 2013), as the Wi-Fi route comprises an untrustworthy and unforeseen medium that can cause severe degradations to the transmitted signal. The limited data transfer usage of the Wi-Fi route in conjunction with the lots of picture and movie data, comprise a very interaction solutions are considerably more difficult, compared to the traditional voice solutions, for which reliable interaction networks have been in place for many years.

One of the major difficulties in interaction systems, and in particular Wi-Fi solutions, is therefore the design of systems that meet the strict Quality of Service (QoS) specifications of Wi-Fi image and video programs to guarantee a certain Quality of Experience (QoE) to the end-user (F.D.Simone et al., 2009). In order to observe the standard of the Wi-Fi interaction solutions, appropriate analytics are needed that are able to perfectly evaluate the end-to-end visible quality as recognized by the customer.

The causing analytics can be utilized to execute efficient web link variation and resource management techniques to meet up with the strict QoS specifications. Traditional web link part analytics, such as Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER), have been widely used to execute this task but were found to not appropriately indicate the subjectively recognized quality (Q.Huynh-Thu et al., 2008), as the impact of transmitting mistakes on the visible indication may differ significantly based on the location of the mistakes in the bit flow (P.Brun et al., 2004, T.Liu et al., 2009).

1.2. The Conventional Image Metrics

With the increasing appearance of digital visible media, quality assessment has been recognized as an important tool for design. Especially, the initiatives in visible quality assessment have improved considerably, leading to a number of quality analytics that have been suggested. However, this research field is considered to be still premature, as there are no commonly approved Image Quality Metric (IQM) and Video Quality Metric (VQM) that work well under a variety of different conditions (T.Liu et al., 2009).

In the areas of conversation and sound, there are two commonly approved methods, one is the Perceptual Evaluation of Speech Quality (PESQ) and the other one is Perceptual Evaluation of Audio Quality (PEAQ). Thus, the traditional constancy analytics such as the Mean Squared Error (MSE) and the related optimum Peak Signal-to-Noise Ratio (PSNR) are still primarily used for tracking program performance. With the developments in perceptual quality assessment, however, the approval of visible quality analytics as an alternative to PSNR is gradually becoming a reality.

To completely understand the benefits of perceptual quality analytics, it is favorable to examine the qualities of the trusted analytics, such as PSNR, and recognize their disadvantages in regards to forecast of recognized visible quality. Pictures and video clips are provided on a digital device in a pixel-based fashion, where each pixel is showed by a luminance value and corresponding chrominance principles. The widely used PSNR, however, assesses the fidelity between two images $I_1(x, y)$ and $I_2(x, y)$ on a pixel-by-pixel basis as given in equation (1.1)

$$\mathrm{PSNR} = 10\log\frac{\eta^2}{\mathrm{MSE}} \tag{1.1}$$

where η *is* the maximum pixel value, typically 255. The MSE is given as given in equation (1.2)

$$\mathrm{MSE} = \frac{1}{\mathrm{XY}}\sum_{x=1}^{X}\sum_{y=1}^{Y}[I_1(x,y) - I_2(x,y)]^2 \tag{1.2}$$

with X and Y denoting the horizontal and vertical image dimensions, respectively. The easy, pixel-based distinction computation is computationally very efficient; however, it is also the primary purpose why PSNR and MSE display in many situations a bad connection with recognized visible quality. This is to say that PSNR does not usually execute poorly, that's why it has thus far been so commonly used, especially in the picture and movie programming group (Q.Huynh-Thu et al., 2008).

1.3. Subjective Image/Video Quality Assessment

The simple, pixel-based analytics can usually be regarded as kind of a 'worst case' scenario in relation to forecast of recognized visible quality. On a range measuring the efficiency in predicting perceptual quality, these analytics therefore represent the lower end. On the other hand, individual experts are usually regarded to be the best judges of visible quality and very subjective evaluation techniques are regarded to be the most reliable actions of recognized visible quality (P.Brun et al., 2004). Subjective evaluation techniques are thus often regarded as a 'ground truth' for quality forecast and hence, form the higher end of a quality forecast efficiency range.

For IQM and VQM to predict recognized visible quality well, very subjective quality ratings are thus needed for the metric design and validation. These are usually obtained by conducting picture and video quality tests, involving a number of individual experts that rate the quality stimuli presented to them. The resulting Mean Opinion Scores (MOS), as an average over all experts, then constitute a very subjective measure of recognized visible quality. There are several international standards that specify in detail the procedures for very subjective picture and video quality tests that should be followed to obtain valid outcomes in terms of MOS.

The most commonly used standards are specified by the International Telecom Union (ITU). As per the Radio communications industry of the ITU (ITU-R) standards, the techniques for television pictures in Rec. BT.500-11 (ITU et al., 2002) were identified such as both dual and individual stimulation methods. In the individual stimulation ongoing quality evaluation method, the quality altered stimulation is ranked without any referrals to the original stimulation. On the other hand, both the referrals and the altered stimulating elements are ranked using the dual stimulation ongoing quality scale. Similarly, techniques for multimedia programs are defined in Rec. P.910 by the Telecoms industry of the ITU (ITU-T), such as an Absolute Classification Ranking (ACR) for individual stimulation evaluation and the Degradation Classification Ranking (DCR) for dual stimulation evaluation.

It is because of these specific techniques that very subjective quality tests are commonly accepted measures of perceptual quality. However, these techniques also require a careful style process, which makes very subjective tests usually tedious and time intensive. The results of subjective quality tests in terms of MOS are instrumental though, for the style and approval of perceptual IQM and VQM. In addition, they provide valuable insight into human visual perception of natural image and video content in the presence and absence of distortions.

With the turn of the century it has been progressively noticed that efficient and precise visible quality analytics can only be obtained through a thorough understanding of individual visible understanding in regards to visible media (N.D.Narvekar et al., 2009). For this reason, several subjective researches were conducted to assess the effect of various system factors on visible understanding. (Z.Yu et al., 2002) analyzed the effect of watching distance on quality understanding and discovered, that there is no factor between two examined watching ranges. (Barkowsky et al., 2009) analyzed the effect of picture demonstration time on the final MOS.

It was discovered that MOS from smaller demonstration periods can perfectly be expected from MOS given after longer demonstration periods. (S.H.Bae et al., 2009) examined the trade-off between spatial quality and quantization disturbance and discovered, that individual experts prefer, to some degree, a lower quality to reduce the exposure of the pressure relics. (C.Zetzsche et al., 1989) conducted early research on the impact of different quantization factors and structure in H.264/AVC movie on the causing quality.

More recently, (M.Ries et al., 2008) analyzed the perceptual quality of H.264/AVC movie containing bundle reduction. (M.H.Pinson et al., 2004) in comparison the very subjective quality variations between H.264/AVC and MPEG-2 for high-definition television, verifying the common perception that H.264/AVC provides similar quality at half the bit amount. (Zhai et al., 2008) discovered that recognized quality is impacted in climbing down order of importance by the encoder type, movie content, bit amount, structure amount, and structure size.

The detectability of artificial preventing, cloud, buzzing, and disturbance relics has been analyzed (M.C.Q.Farias et al. 2007) in a sequence of tests. Amongst other results, it was determined that mistake exposure and recognized irritation are highly associated. The exposure of different types of disturbance in natural pictures has been analyzed (S. Winkler et al., 2004), who determined that the disturbance limits increase significantly with picture activity. (R.R.Pastrana-Vidal et al., 2006) revealed in their study, that overall recognized movie quality can be approximated from separate spatial (sharpness) and temporary (fluidity) quality decisions.

(Q.Huynh-Thu et al., 2008) analyzed the effect of temporary relics in movie and discovered that quality understanding is more seriously suffering from jitter as in comparison to jerkiness relics. (T.Liu et al. 2009) examined the effect of various bundle reduction styles, considering the reduction duration, regularity, and temporary location based on PSNR actions. It was determined that quality reduces linearly with reduction duration and is preservative based on the variety of failures. (G.W.Cermak et al., 2009) interviewed people about the appropriate variety of situations in consumer movie. It came out that on average customers would not accept relics to be more regular than once an hour, unless, the service cost is considerably reduced.

These studies emphasize the many impacting aspects that impact on the individual understanding of visible quality. Integrating all these aspects into a quality measurement would likely result in a measurement that shows well the individual visible understanding of quality. However, such a measurement would also be highly complex and computationally expensive, thus finding little use in many applications that have strict boundaries on computational complexness.

To support reproducible research and to allow for quality metric design and approval, several picture and movie quality database have been created openly available. These databases usually consist of the stimuli that were presented during the subjective experiment and the quality scores that were obtained from the human experts. Probably the most widely used picture quality database are the MICT database (Z.M.P.Sazzad et al., 2010), the IRCCyN/IVC database (P.Le Callet et al., 2005), and the LIVE database (H.R.Sheik et al., 2005), which are based on the assessment of distorted pictures mainly containing source programming relics and synthetic relics such as white-noise. More lately the elaborate TID picture quality database has been available (N.Ponomarenko et al., 2009), which covers a wide range of relics and provides MOS based on hundreds of experts. The latest picture quality databases are the CSIQ (D.M.Chandler et al., 2010), containing pictures with source programming disturbances and synthetic disturbance. For many years, the FRTV Phase I database by the Video Quality Experts Group (VQEG) was the only available movie quality database and has thus extensively been used for VQM design and approval. This has been changed lately with several video quality databases which was openly available. The NYU database contains video clips with packet loss disturbances. Two LIVE video quality databases are further available of which one database contains video clips with both compression and transmitting disturbances whereas the other database is focused on Wi-Fi communications disturbances. The EPFL-PoliMi video quality database (F.De Simone et al., 2009) has been created, focusing on transmitting disturbances. The latest release is the EPFL 3D movie quality database, allowing for upcoming 3D VQM to be designed and validated on.

1.4. Visible Quality Analytics

Visible quality analytics can usually be described with regard to two different main aspects that are regarded in the measurement style process:

1. The underlying knowledge and assumptions about the HVS.
2. The scope of visual distortions that are accounted for by the quality metric.

This difference is portrayed with the two primary aspects being highlighted by these aspects.

Factor 1: Human Visual System: Perceptual visible great quality analytics aim to imitate the understanding of an individual viewer and as such, it is user-friendly to integrate features of the HVS into the measurement design process (X.Zhu et al., 2010). This can be done to different levels of complexness, which range from only simple estimates of some appropriate HVS qualities to very complicated techniques integrating precise designs of the HVS. In common, one can say that more complicated techniques often result in better great quality forecast efficiency, which comes at the price of greater computational price. As recommended in (H.Liu et al., 2010), HVS-based analytics are usually developed with regard to either a bottom-up or a top-down viewpoint. Following the former strategy, the features of the different HVS elements are calculated by computational methods and incorporated into a natural design of recognized great quality.

The aim of this strategy is to develop a computational design that features in identical way as the important areas of the HVS that are engaged in great quality understanding. On the other hand, analytics following the top-down viewpoint do not aim to imitate each HVS element individually, but are depending on advanced stage presumptions about great quality handling in the HVS (R.Soundararajan et al., 2013). As such, the HVS is handled as a dark box and the input-output regards is targeted on, instead of the features of the HVS. The boundary between the two concepts is unclear and great quality analytics can integrate both, particular features of the HVS and also advanced stage presumptions about the great quality understanding in the HVS.

Factor 2: Visual distortions: Based on what distortions types are included, perceptual quality analytics can further be classified into common objective analytics and program particular analytics. General objective designs, also sometimes referred to as worldwide designs, do not create any particular presumptions regarding the disturbances in the visible material.

As such, these analytics often focus on common features, such as natural scene research (sheikh et al., 2005), and usually follow a HVS related style, with the aim of implementation in a variety of programs. On the contrary, program particular analytics have particular information about disturbances or create presumptions about disturbances that can be expected in the visible material. This information generally helps to make simpler the measurement style and to improve quality forecast efficiency for the particular program. At the cost of worse efficiency, when implemented in a different perspective than the need for growing quality assessment. The measurement has been intended to get the good quality of the image. These analytics would perform badly if used, for instance, to evaluate JPEG2000 pictures, which contain considerably different disturbances.

1.5. HVS based Assessment

To provide an introduction to the developments in visible quality evaluation thus far, it emphasizes in the following some of the objectives and evaluation some of the significant efforts. After assessing the early works, it looks in particular at the developments in FR, NR, and RR quality evaluation.

Early perform goes back several decades with great quality designs being developed for black and white pictures by Mannos and Sakrison and for black and white movie series by (F. Lukas et al., 1982). The knowledgeable important improvements in the 1990's and at the turn of the millennium, with essential execute on complex HVS-based quality styles The Noticeable Variations Forecaster by (S.Daly et al., 1993) calculated picture constancy as a function of display factors and watching conditions. The VDP was later tailored by (A.Bradley et al., 1999) particularly for wavelet centered programs. (P.C.Teo et al., 1994) suggested a distortions measure in accordance with the steerable chart convert and comparison normalization.

(C.J.Van den Branden Lambrecht et al., 1996) described a multi-channel design of individual spatio-temporal perspective, specifically parameterized for movie. The more general Sarnoff design suggested by Lubin actions JND in visible stimulating elements, depending on psychophysical concepts of individual visible elegance performance. (S.Winkler et al., 1998) suggested a PDM both for color pictures and for color movie, depending on several qualities of the HVS, such as color understanding.

The Digital Video Quality (DVQ) metric by (Watson et al., 2001) is depending on an intricate HVS design and was revealed to perform in the same way well to the Sarnoff JND design. Martens performed multidimensional modeling to account for different factors that impact on the overall great quality reasoning. This was in accordance with the speculation that the applying from joint multidimensional features to single overall great quality reasoning may differ considerably between individual experts. Similar to the remarkable initiatives towards finding possible designs of individual visible understanding, research initiatives were still continuous towards simple mathematical analytics.

This was likely motivated by the great computational complexness of the HVS designs and the computational restrictions of most picture and movie handling systems. Towards the end of the 1990's, the pattern then shifted somewhat away from the intricate HVS-based analytics (bottom-up approach) towards more technological innovation motivated analytics that often integrate some advanced level presumptions about the HVS (top-down approach).

In the past several years, several FR analytics have been suggested that are expected to have a good connection with human understanding due to the accessibility to the referrals image/video. Even though these analytics find only little use for application in interaction viewpoint, it includes some major efforts in this research for completeness. The Picture quality Range (T.Yamashita et al., 2000) is based on a variety of spatial and temporary features produced from movie, such as jitter, sparkle, disturbance, and cloud. A blockiness sensor for MPEG movie is suggested (H.Tang et al., 2011). Besides the preventing removal this measurement also has a simple perceptual design. The SSIM catalog (Wang et al. 2011) is in accordance with the supposition that the HVS is tailored to removal of structural rather than pixel details. The SSIM catalog is these days probably the most widely used picture quality measurement which can be linked to its well balanced bargain between complexness and quality forecast efficiency.

The Visible Information Constancy requirements (Sheikh et al., 2006) techniques the standard forecast problem from details theoretic viewpoint. The VIF requirements has been developed in the same group as the SSIM catalog and is actually often excellent to SSIM, which comes at the cost of higher computational complexness. The Visible Disturbances Evaluate (W.Lin et al., 2005) is based on local comparison changes and has been found to be particularly effective in calculating cloud relics and luminance modifications. The Visible Signal-to-Noise Ratio (VSNR) by Tempe and Hemami deploys a two-stage approach, with the first level identifying a distortion recognition limit. If the distortions are suprathreshold, then the VSNR is calculated based on recognized comparison and international priority qualities of the HVS.

The Most Obvious Disturbances measurement (E.C.Larson et al., 2010) is in accordance with the supposition that the HVS deploys different strategies for identifying picture quality, based on if the visual distortions are near-threshold or suprathreshold. Thus, the design records for a detection-based technique in the very best pictures and an appearance-based technique in poor pictures. The measurement suggested (A.C Bovik et al., 2010) expands the current SSIM index by a three-stage design to consideration for different groups of local content; sleek areas, distinctive areas, and edge areas.

The effects of temporary characteristics in video, both from material and a distortion viewpoint, have progressively been resolved in quality measurement design. A temporary modification factor is implemented in perform, in addition to a pressure distortion measurement, to consideration also for the effect of structure amount on the overall recognized quality. The measurement (H.Liu et al. 2010) records for both, degradations through source programming and bundle reduction. Several factors are incorporated into the measurement with regards to their effect on the overall recognized quality, such as the reduction length, the reduction intensity, reduction location, the variety of failures, and the reduction styles.

The temporary modifications of distortions are included in the performance (Ninassi et al. 2009) by implementing short-term and long-term temporary combining techniques. In particular, the short-term combining was recognized to be essential for helping the standard forecast efficiency of the measurement. The Temporal Velocity Aware Video Quality Measure by (Barkowsky et al., et al., 2009) also mainly concentrates on temporary issues, such as structure gets frozen and the requirement for, structure amount reduction, impact of field reduces, and the monitoring of the exposure of altered things. The Motion-based Video Quality Assessment, by (Seshadrinathan et al., 2010) includes both spatial and temporary distortion actions, but concentrates in particular on analyzing movement quality along calculated movement trajectories.

There have not been as many successful attempts to define NR quality analytics, in comparison to the number of FR designs that have been suggested. It is more trial of quality forecast without any referrals. To help make the NR measurement design more responsive, most designs are in fact designed to serve particular applications for which the expected disturbances are known. A NR quality measurement for JPEG pictures is suggested (Wang et al. 2011). The measurement focuses on preventing relics, given their predominance in JPEG compressed pictures, and takes cloud ultimately into account. The quality forecast performance of the work has been significantly improved (Y.Horita et al. 2006) through the introduction of regional function computations. A simple quality model for MPEG-4 movie, depending on frame amount and bit amount actions, has been suggested by (H.Koumaras et al. 2005).

A NR VQM in accordance with the variations of regional regions between two successive frames is suggested by (Yang et al., 2005). These variations are weighted according to the temporal activity in video. A quality measurement depending on motion characteristics and content category is suggested by (M.Ries et al., 2008) for H.264 video, low-resolution movie sequences. (T.Liu et al., 2009) suggested a quality measurement for JPEG and JPEG2000 pictures, depending on nearby gradient statistics. In addition to these particular NR quality analytics, there are numerous analytics that are depending on single function.

The most commonly addressed relics include preventing, cloud, ringing, and sharpness. A measurement mixing synthetic preventing, cloud, and noise relics is suggested (Watson et al., 1997). The survey of NR quality evaluation reveals that the analytics are program particular or even particular. Quality shows that it is still a long way towards truly universal NR picture quality analytics.

1.6. Visual Attention for Quality Assessment

Although the number and range of visible quality analytics that have been suggested thus far is large, most of them do not take into account a fundamental element of the HVS that can be believed to have a major effect on the understanding of overall recognized picture and video quality. This HVS property is generally known as visible interest (S.Daly et al., 1993) and includes higher intellectual handling implemented to reduce the complexness of area research. For this purpose, a part of the available visible details is chosen by moving the concentrate of interest across the visible area to the most significant things. It is because of the VA systems that the HVS is able to deal with the numerous amounts of visible details that it is encountered with at any immediate in time.

Integrating designs of VA into visible quality evaluation can thus be believed to be very valuable, since the audience may be more likely to identify relics in extremely significant areas, as compared to areas of low saliency. This is further reinforced by the fact that the feedback level of the HVS, the retina, is extremely space version in testing and handling of visible alerts. The biggest precision is in the main point of concentrate, the fovea, and highly decreases towards the outside of the visible area. As such, disturbances in extremely significant areas may be recognized in more details and consequently, as being more frustrating than disturbances in areas of low saliency.

1.7. Objectives and Scope of the present work

The goal of this work is to evaluate the quality of JPEG2000 images and H.264 videos based on Human Visual System using No Reference Distortions Patch Feature Image/Video quality evaluation criteria approach. This analysis involves:

1. To implement the No Reference Distortion Patch Features Image Quality assessment algorithm based on HVS [A-6].
2. To develop an algorithm for No Reference Image Quality Assessment for JPEG2000 images based on Human Visual System [A-4].
3. To analyze the performance of No Reference Image Quality based on Human Perception [A-3].
4. To study the informal complexity analysis of Image Quality based on HVS [A-5].
5. To implement the No Reference Distortion Patch Features Video Quality Assessment algorithm for H.264 videos based on Human Visual System [A-7].
6. To study the Low bit rate Video Quality Analysis Using NRDPF-VQA algorithm [A-1].

7. To study the visually lossless level Video Quality Assessment using NRDPF-VQA algorithm [A-2].

1.8. Organization of the Thesis

The thesis is organized into five chapters as follows

Chapter-1: Introduction, subjective data analysis, research motivation and objectives are presented in this chapter.

Chapter-2: This chapter covers the survey of literature pertaining to the no reference image/video quality assessment.

Chapter-3: This chapter introduces No Reference image quality assessment for JPEG2000 and experimental results using other image databases using NRDPF-IQA method.

Chapter-4: This chapter introduces No Reference video quality assessment for H.264 and experimental results using other video databases using NRDPF-VQA method.

Chapter-5: This chapter concludes the research work that has been carried and presents the future scope of the work done.

The overall image/video quality assessment scenario can be described as shown in the flow chart.

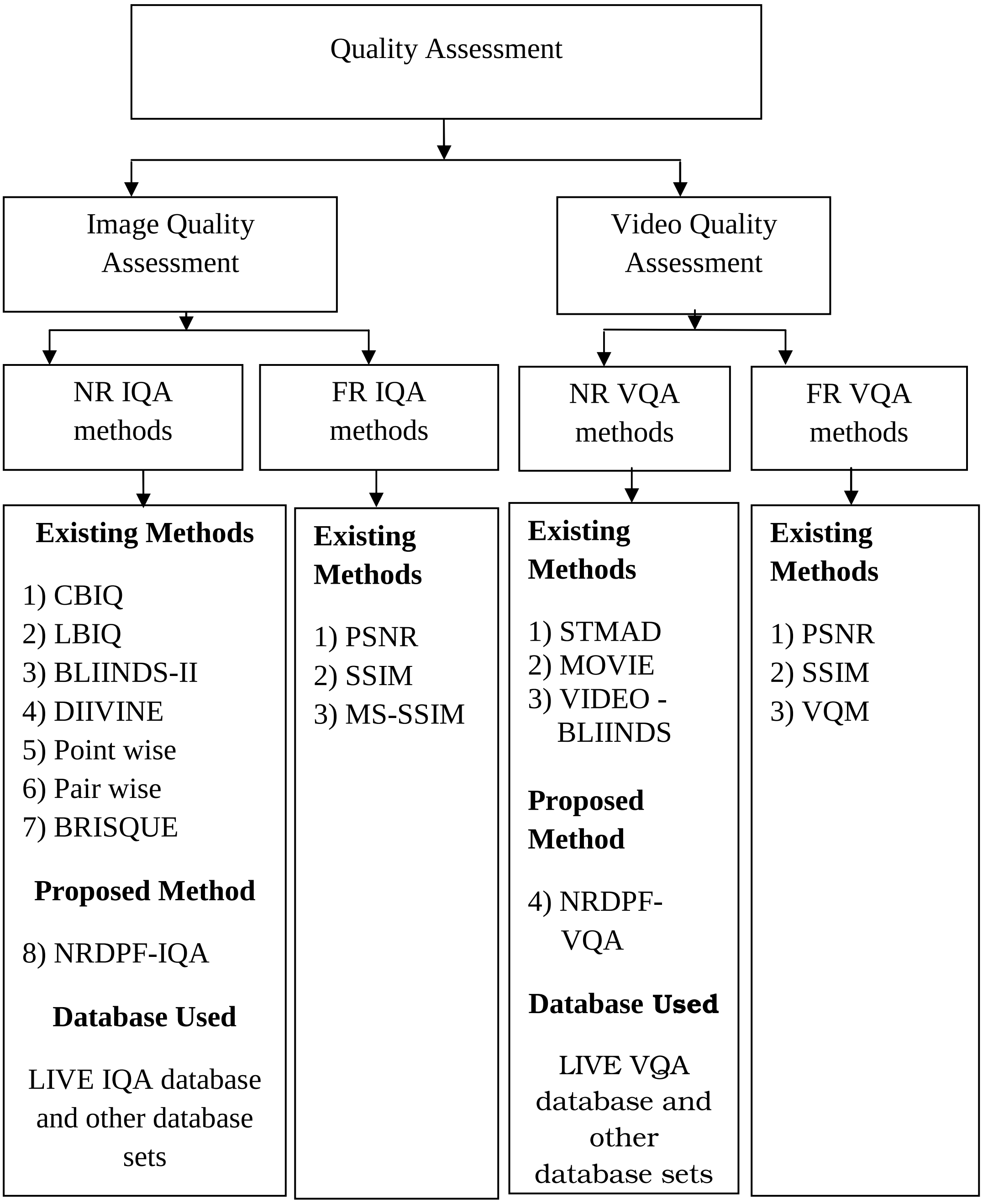

Fig.1.1. Image/Video quality assessment scenario

Chapter-2

REVIEW OF LITERATURE

2. REVIEW OF LITERATURE

2.1. Introduction

The survey of literature starting from the historical background and the developments in image and video quality assessment, with main emphasis on the development of quality assessment based on Human Visual System and their related issues are dealt in this chapter. Existing modeling methods for the analysis of various images and videos were also thoroughly reviewed. The literature available on QA, a No-Reference algorithm approach for modeling of image and video quality assessments are also dealt in this chapter.

With the release of networked portable devices which can catch, store, pack, send and display a wide range of audio visual stimuli; high-definition television (HDTV); loading IP address TV (IPTV) and websites such as youtube.com, Facebook and Rediff etc., quantity of visible information of visible information is making its way to consumers. Because of this, efforts and resources are being extended to ensure that the end customer is presented with acceptable Quality of Experience (QoE) (F.D.Simone et al., 2009). While traditional QoE methods have focused on improving distribution networks with regard to throughput, buffer-lengths and capacity, perceptually enhanced distribution of multi-media services is also quick gaining importance. This is especially appropriate given the intense growth in (especially wireless) video traffic and expected deficits in data transfer usage. These perceptual techniques attempt to provide an enhanced QoE to the end-user by utilizing purpose actions of visible great quality.

Subjective referenceless or No-reference (NR) picture great quality evaluation represents automated great quality evaluation of picture using an criteria such that the only details that the criteria gets before it makes a forecast on great quality is the altered picture whose great quality is being evaluated. On the other end of the wide range lie full-reference (FR) methods that need as feedback not only the altered picture, but also a ‘clean’, breathtaking referrals picture with regard to which the altered picture is evaluated. Somewhere between these two extreme conditions lie reduced-reference (RR) techniques that have some details regarding the referrals picture (eg., a watermark), but not the actual referrals picture itself, apart from the altered picture (F.Lukas et al., 1982).

The strategy to NR IQA is in accordance with the key that organic pictures have certain regular mathematical properties that are measurably customized by the existence of disturbances. The stabilized luminance coefficients of the organic picture closely follow

Gaussian-distribution, while the same does not hold for the scientific submission of the synthetic picture. Diversions from the regularity of organic research, when quantified properly, enable the design of methods able of evaluating the perceptual quality of picture without the need for any referrals picture.

By quantifying organic picture research and staying away from precise depiction of disturbances, the strategy to great quality evaluation is not restricted by the type of disturbances that affect the picture. Such techniques to NR IQA are important since most current techniques are distortion-specific (E.C.Larson et al., 2010), i.e., they are able of performing sightless IQA only if the disturbances that affects the picture is known beforehand, e.g., cloud or disturbance or pressure.

Previously, other NSS-based distortion-generic techniques to NR IQA that mathematically design pictures in the wavelet-domain (D.M.Chandler et al., 2007) and in the DCT-domain (M.A.Saad et al., 2012) are studied. The participation here is a new NR IQA design that is simply spatial, that depends on a spatial NSS design which does not need a applying to a different co-ordinate sector (wavelet, DCT, etc.) and so is 'transform-free', that shows better ability to estimate individual decision of great quality than other well-known FR and NR IQA models, that is extremely efficient, and that is useful for perceptually improving picture handling methods such as denoising.

2.2. Image and Video Quality Assessment

The growing approval and use of mobile Wi-Fi gadgets has become a major focus of handling the Wi-Fi system facilities that was initially designed for speech and low-level data, due to blast of great bit rate material in the form of great data transfer usage pictures and videos (K.Sharifi et al., 1995). This presents an exciting process to change the service quality in terms of Quality of Experience (QoE) at the end customer - a trial - since QoE not only relies on the time different characteristics of the route due to following their every move, powerful disturbance, flexibility, and modifying plenty but also on a wide range of other aspects, such as the material, quantity of pressure and the powerful characteristics of the videos (M.Barkowsky et al., 2009). For example, the QoE might be considered as inadequate for a high-motion action field, while that of a low-motion field may be appropriate under the same route circumstances.

Modeling each of these aspects independently is not only complicated but also incorrect. A different, highly realistic solution is that of abstracting these modifications away, by trying to evaluate the QoE from the viewpoint of the end customer (Zetzsehe et al., 1989).

This is obtained using innovative designs of human visual understanding and the mathematical qualities of the video clips are being considered. In this research, it shall cover a wide range of such methods that estimate overall QoE of a picture and video, based on the quantity of information available for the criteria design.

The efficiency of any IQA model is best gauged by its connection with individual very subjective judgements of quality, since the individual is the ultimate receiver of the visible indication. Such individual views of visible quality are usually acquired by conducting large-scale scientific testing on people, referred to as very subjective quality evaluation, where individual observers rate a huge number of distorted (and possibly reference) signals (A.B.Watson et al., 2001). When the person opinions are averaged across the topics, a mean perspective position or differential mean perspective position is obtained for each of the noticeable signals in the research, where the MOS/DMOS is representative of the perceptual great organization's noticeable indication. The goal of subjective quality evaluation (QA) criteria is to predict quality ratings for these alerts such that the ratings produced by the criteria correlate well with individual views of indication quality (MOS/DMOS).

Program of QA methods requires that these methods compute perceptual quality efficiently. The Spearman’s rank ordered correlation coefficient (SROCC) and Pearson’s (linear) correlation coefficient (LCC) between the predicted ranking from the criteria and DMOS are usually used to access QA efficiency. The participation is the growth of a NRDPF-IQA style, leading to neither a first of a type NR IQA style which does not need contact with altered pictures a priori, nor any training on individual viewpoint ratings. The new NRDPF-IQA quality index works better than the well-known FR peak signal-to-noise-ratio (PSNR) and structural similarity (SSIM) index and provides efficiency at par with executing NR IQA approaches (Anish Mittal et al., 2012).

Further, it observes that models are also restricted. They can only catch common guideline features of a particular choice of non-distorted material. Those do not globally signify material particular implicit features. Also, the growth of such a data source needs the impartial choice and servicing of thousands of natural undistorted material (A.M.Eskicioglu et al., 1995).

Most current referenceless IQA designs suggested in previous times assume that the picture whose great quality is being evaluated is affected by a particular kind of disturbances (K.Sharifi et al., 1995). These techniques extract distortion-specific functions that report to lack of visible great quality, such as edge-strength at block boundaries.

However, a few general purpose techniques for NR IQA have been suggested lately. (Lee et al., 2007) developed a set of heuristic actions to define visible great quality in terms of advantage sharpness, unique disturbance and architectural disturbance while (S.Gabarda et al., 2007), made anisotropies in pictures using Renyi entropy. (P.Ye et al., 2011) use gabor filter centered regional appearance descriptors to type a visible codebook, and understand DMOS ranking vector, connecting each word with a higher quality ranking. However, in the procedure of visible codebook development, each function vector associated with picture spot is marked by DMOS allocated to the entire picture. This is doubtful as each picture spot can present a different great quality based on the disturbances procedure the picture is affected with.

In particular, regional disturbances such as bundle reduction might affect only a few picture areas. Also, the strategy is computationally expensive restricting its usefulness immediately programs. (R.Ferzli et al., 2009) suggested a strategy which understands collection of regressors trained on three different groups of functions - organic picture research, disturbances structure research and blur/noise research. Another strategy (S.H.Bae et al., 2009) is based on a multiple of curvelet, wavelet and cosine converts. Although these techniques perform on a wide range of disturbances, each set of functions and converts serves only to certain kinds of disturbances processes.

Previous NR QA designs are studied, following are the viewpoints, first fully designed in (S.Suthaharan et al., 2009), that NSS designs provide powerful tools for searching individual decisions of visible disturbances. The performance on NSS centered FR QA methods (S.Winkler et al., 2004) more latest RR designs (Soundararajan et al., 2012) and very latest perform on NSS centered NR QA (Wang et al., 2011) have led us to the conclusion that visible functions based on NSS lead to particularly effective and simple QA designs (A.K.Murthy et al., 2011). The NSS centered NR IQA design, known as the Distortion Identification-based Image INtegrity and Verity Evaluation (DIIVINE) catalog, deploys conclusion research based on an NSS wavelet coefficient design, using a two level structure for QA: distortion-identification followed by distortion-specific QA (A.K.Murthy et al., 2011).

The DIIVINE catalog works quite well on the LIVE IQA database (H.R.Sheikh et al., 2005), achieving mathematical equality with the full-reference SSIM index (Z.Wang et al., 2004). A supporting strategy designed simultaneously; named BLind Image Notator using DCT Statistics (BLIINDS-II index) is realistic strategies to NR IQA that operates in the DCT sector, where some functions are calculated from an NSS design of prevent DCT coefficients (M.A.Saad et al., 2012). Effective NSS functions are measured and fed to a regression operate that provides precise QA forecasts. BLIINDS-II is a single-stage criterion that also provides extremely aggressive QA forecast energy. Although BLIINDS-II catalog is multiscale, the few of function types (4) allow for efficient calculations of visible great quality and hence the catalog is attractive for realistic programs.

While both DIIVINE and BLIINDS-II provides NR IQA efficiency, each of them has certain restrictions. The lots of functions that DIIVINE determines indicate that it may be difficult to estimate immediately. Although BLIINDS-II is more effective than DIIVINE, it needs nonlinear organizing of prevent centered NSS functions, which decreases it considerably.

In ongoing search for quick and efficient rated NSS centered NR QA spiders, it has analyzed the possibility of developing distortion path feature designs that operate directly on the spatial pixel information. The motivation for thinking it may succeed, is the revolutionary perform by (Ninassi et al., 2009) on spatial organic field modeling, and the success of the spatial multi-scale SSIM catalog (Z.Wang et al., 2003), which plays well with convert sector IQA designs.

While the existence of referrals, the images details are regarding the referrals. It makes easier the problem of great quality evaluation. The realistic programs of such methods are restricted in real-world circumstances where referrals details are usually not available at nodes. The great quality calculations are performed. Further, it can be suggested that FR and to a huge extent RR techniques are not great quality actions in the true sense, since these techniques evaluate constancy relative to a referrals picture. Moreover, the supposition of a breathtaking nature of any referrals is doubtful, since all pictures are evidently altered (E.C.Larson et al., 2010).

The efficiency of any IQA design is best measured by its connection with individual very subjective decisions of great quality, since the individual is the ultimate recipient of the visible indication. Such individual views of visible great quality are usually acquired by performing large-scale scientific testing on people, referred to as very subjective great quality evaluation, where individual experts rate a huge wide range of altered alerts.

When the individual views are averaged across the topics, a mean viewpoint ranking or differential mean viewpoint ranking is acquired for each of the visible alerts in the study, where the MOS/DMOS is representative of the perceptual great quality visible indication. The goal of purpose great quality evaluation (QA) criteria is to estimate great quality ratings for these alerts such that the ratings produced by the criteria link well with individual views of indication great quality (MOS/DMOS).

The regularity of research has been well established in the visible science literary works, where regularity has been confirmed in the spatial sector (P.V.Vu et al., 2011), and in the wavelet sector (Watson et al., 1997). For example, it is well known that the energy wide range of organic pictures is operate of regularity and takes the type 1/ f_{γ}, where γ is an exponent that differs over a little range across organic pictures. The product of earlier research is the Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE) which uses an NSS design structure of regionally stabilized luminance coefficients and quantifies 'naturalness' using the factors of the design.

NRDPF-IQA/VQA presents a new design of the research of pair-wise difference items of nearby luminance principles. The factors of this design further evaluate the naturalness of the picture. The intension is that characterizing regionally stabilized luminance coefficients in this way is sufficient not only to evaluate naturalness, but also to evaluate great quality in the existence of disturbances.

2.3. JPEG2000 Images and H.264 Videos

JPEG2000 is a wavelet-based picture pressure conventional. It was designed by the Joint Photographic Professionals Team panel in 2000 with the objective of superseding their unique distinct cosine transform-based JPEG conventional (created 1992). The standardized filename expansion is .jp2 for ISO/IEC 15444-1 contouring information and .jpx for the extended part-2 requirements, released as ISO/IEC 15444-2, while the MIME kind is image/jp2.

While there is a moderate improve in pressure efficiency of JPEG2000 in comparison to JPEG, the primary benefits provided by JPEG2000 is the important versatility of the code stream. The code stream acquired after pressure of picture with JPEG2000 is scalable in characteristics, significance that it can be decoded in a variety of ways; for example, by truncating the code stream at any factor, one may acquire a reflection of the picture at a lower quality, or signal-to-noise rate. By purchasing the code stream in various methods, applications can accomplish important efficiency improves. However, as impact of this versatility, JPEG2000 needs encoders/decoders that are complicated and computationally demanding. Another distinction, in evaluation with JPEG, is with regards to visible artifacts: JPEG2000 generates buzzing relics, demonstrated as cloud and jewelry near sides in the picture, while JPEG generates buzzing relics and 'blocking' relics, due to its 8×8 prevents. JPEG2000 has been released as an ISO conventional, ISO/IEC 15444.

The mathematical design of regionally stabilized luminance coefficients in the spatial sector was studied, as well as the design for couple sensible items of these coefficients. The efficiency of NRDPF-IQA/VQA is thoroughly verified, and mathematically evaluates NRDPF efficiency to state-of-the-art FR and NR IQA techniques. NRDPF-IQA/VQA is extremely aggressive to these NR IQA/VQA techniques, and also mathematically better than the well-known full-reference peak signal-to-noise ratio (PSNR) and SSIM. NRDPF-IQA/VQA works well on separate database like JPEG2000 evaluate its complexness and evaluate it with other NR IQA techniques for JPEG2000. Finally, the realistic importance of NRDPF-IQA is demonstrated, how a no reference picture denoising algorithm can be enhanced with NRDPF-IQA in order to improve sightless picture denoising is explained. Results display that NRDPF-IQA enhancement leads to important efficiency developments over the state-of-the-art.

Electronic video clips are increasingly finding their way into the day-to-day lives of people via the explosion of movie programs such as digital television, digital cinema, Internet video clips, movie teleconferencing, video-sharing services such as YouTube, Video on Demand (VoD), home video clips, and so on. Electronic video clips typically successfully go through several handling levels before they achieve the end customer of video clip. Most often, this end customer is an individual observer. In order to transmit video clips over narrow band network it is necessary to decrease the size of original movie. Electronic video clips successfully go through several handling levels before they achieve the end customer of video clip. Different pressure techniques like H.263, H.264 are used to reduce the bandwidth usage required and also the storage space potential. One of the effects of handling of movie is degradation of movie quality due to distortions.

Since individual observers at the receiver side are sensitive to video clip quality, for many programs, such as movie conferences and broadcasting, it is important to have a good estimate of the quality material being received. Techniques for evaluating movie quality play a critical role in quality monitoring to maintain Quality of Service (QoS) requirements.

Subjective VQA deals with techniques that utilize individual subjects to perform the task of evaluating visual quality. Very subjective VQA is impractical for most programs due to the individual involvement in the process. The Mean Opinion Score (MOS) is measured as sum of their ratings which is evaluated of very subjective quality evaluation. Video quality is affected by watching conditions such as normal lighting, display device, watching range and so on and very subjective studies have to be performed in a properly managed atmosphere. Hence it is a complicated process.

The major disadvantage of the FR approach is that it requires a lot of referrals details at the final comparison point. RR analytics may be less precise than the FR analytics, but they are also less complex, and make real-time implementations more affordable. Need for the referrals movie or an even limited detail about it becomes a serious barrier in many real-time applications. It is essential to develop NR movie quality analytics that thoughtlessly calculate the quality of videos clip.

Previous NR VQA designs in the past were studied, following are the viewpoints, first fully designed in (T.Liu et al., 2009), that NSS designs provide powerful tools for searching human decisions of visible disturbances. NSS centered FR VQA methods (T.N.Pappas et al., 2005), more latest RR designs (Soundararajan et al., 2012) and very latest work on NSS centered NR VQA (a.C.Bovik et al., 2013) have led us to the summary that visible functions based on NSS lead to particularly effective and simple VQA designs (C.Chen et al., 2013). Recently suggested NSS centered NR VQA design, known as VIDEO BLIINDS, deploys summary research based on an NSS wavelet coefficient design, using a two level structure for VQA: distortion-identification followed by distortion-specific VQA (Michele A.Saad et al., 2014). An assessment technique designed at the same time; known as Video-BLIINDS index is genuine ways to NR VQA that features in the DCT sector, where some features are measured from an NSS design of avoid DCT coefficients (M.A.Saad et al., 2012).

A supporting strategy designed at the same time; known as Video-BLIINDS index is realistic strategies to NR VQA that functions in the DCT domain, where some functions are calculated from an NSS design of prevent DCT coefficients (M.A.Saad et al., 2012). Effective NSS functions are measured and fed to a regression function that provides precise VQA forecasts. Video-BLIINDS is a single-stage criterion that also provides highly aggressive VQA forecast power. Although Video-BLIINDS catalog is multiscale, the few of feature types (4) allow for efficient calculations of visible quality and hence the catalog is eye-catching for practical programs. While both STMAD and Video-BLIINDS provide NR VQA efficiency, each of them has certain restrictions (Michele A.Saad et al., 2014). The large amount of functions that Video-BLIINDS determines indicates that it may be difficult to estimate immediately. Although Video-BLIINDS is more effective than STMAD, it requires nonlinear organizing of prevent centered NSS functions, which decreases it significantly. In ongoing search for fast and efficient rated NR-VQA spiders, it has designed NRDPF-VQA criteria to find the quality of it without referrals.

The goal of each no-reference approach is to create an estimator that would estimate the Mean Opinion Score (MOS) of human experts, without using original data. There are various improvements done in order to obtain a NR measurement that will show better usefulness. Many analytics considered the most common relics that are seen in videos such as blockiness, cloud or ringing. Some analytics used for picture quality evaluation can also be used for movie quality evaluation. But these analytics are useful for calculating quality of single supports. However, in case of movie there exist temporary changes which are essential to calculate video clip quality and the influence of various disturbances.

There are many studies carried on to create a better quality measurement. A new method for purpose VQA from programming factors of an H.264/AVC bit stream as a hybrid/bit stream classification concentrates on the impact of quantization and de-blocking process, but forgets the distortions due to other factors. Another NR quality measurement uses intra 4x4 prevent method parameter to estimate the spatial difference. Intra 4x4 prevent method is not provided in all bit streams. Also quantized Distinct Cosine Convert (DCT) coefficients produced from bit streams were used to measure the Peak Signal-to-Noise Ratio (PSNR) of movie.

PSNR is not an efficient VQA device, and the function of DCT coefficients would increase the calculations complexness. The additional actions were provided that took into account two movement strength actions i.e. international movement strength, measured from the international movement field, and item movement strength, measured by subtracting the international movement from the movement vectors . A NR quality measurement to evaluate the networked movie, the value of average bit rate per pixel is used to estimate the spatial and temporary complexness. But this value differs extremely with the change of the encoder and its criteria, which could not indicate the spatial and temporary features of movie precisely.

To play the compacted data file, an inverse criteria is applied to produce videos clip that shows virtually the same content as the original resource movie. The mathematical analysis of movie alerts indicates that there is a strong connection both between subsequent mirrors and within the image elements themselves. The traditional approach to film development removes redundancies that exist within individual pictures of each film structure and also between following facilitates. This is achieved by using movement evaluation and settlement H.264 takes movie pressure technological innovation to a new level. Different movie pressure requirements utilize different methods of reducing data, and hence, results differ in bit rate, quality and latency.

Primary of the H.264 standard is to provide a means to achieve considerably higher movie quality compared to what could be achieved using any of the current movie programming requirements. H.264 includes following stages:

1. Dividing each video frame into blocks of pixels so that processing of the video frame can be conducted at the block level
2. Exploiting the spatial redundancies that exist within the video frame by coding some of the original blocks through transform, quantization and entropy coding (or variable-length coding)
3. Exploiting the temporal dependencies that exist between blocks in successive frames, so that only changes between successive frames need to be encoded.

This is achieved by using movement evaluation and settlement H.264 takes movie pressure technological innovation to a new level. H.264/AVC symbolizes a number of developments in traditional movie growth technology, with regards to both growth performance improvement and versatility for effective use over a variety of system types and program sites. With H.264, a new and innovative intra forecast plan is presented for development I-frames. This plan can lower the bit sizing an I-frame and sustain quality by enabling the following prediction of more compact stops of p within each macroblock in a framework. This is done by trying to find related p among the previously secured p that boundary a new 4x4 pixel prevent to be intra-coded. By recycling pixel principles that have already been secured, the bit dimension can be significantly reduced.

2.4. Compressed domain Video Quality Metric

In order to give an appropriate verdict on videos affected by disturbances due to the stress process, it is necessary to evaluate the methods used in film stress methods which could impact the quality compressed videos. Video pressure consists of blocks like movement compensation, movement evaluation, quantization and entropy coding. Quantization causes major amount of distortions in video clip. Quantization causes several spatial and temporary distortions like clouding and ringing effects. Motion also has a crucial role in individual perception. To estimate video clip quality the forehead characteristics of video clip are reflected by the movement vectors and the movement evaluation. Bit rate control scheme is used to spend limited bit streams the region of interest (ROI) of individual viewer. This is to increase video clip quality. Hence, the quantization parameter, the movement and the bit allowance are key factors that are to be used to measure the quality of movie in compacted domain.

2.5. Quantization Parameter Factor

As Quantization Parameter (QP) improves, the deterioration of video improves. Mathematical concepts of DMOS indicate the relative very subjective quality ranking which has a range between [0, 1], where “0” and “1” represent the best and the most serious of the very subjective quality respectively. The video clips with extreme movement suffer from more severe disturbances. Typical human visual system (HVS) based VAQ methods evaluate the spatial and temporary complexness independently, and the outcomes are being used in purpose quality evaluation.

Pressure actually happens during the quantization procedure. The quantization parameter is used for identifying the quantization of convert coefficients. An easy presentation of the individual visible program is that it functions similar to a dig cam, catching the globe around us and transferring the information onto the mind which in turn produces sources of visible stimulating elements that form an ongoing story. However, seeing in itself is a fraud. While the individual visible program is just like a dig cam, and, the eye is indeed a lens-sensor-processor arrangement, individual perspective goes beyond the simple entertainment around the globe that current cameras offer.

Decoding a procession of mild and details using a huge number of distinct nerves and photoreceptors has required the progress of brilliant testing and evaluation strategies, so that the loss of details does not cause to essential difficulties. A lighting example is that of individual shade understanding. The individual retina subsamples the entire shade variety using just three wide types of shade receptor spool cells, which indicates that different mild spectra generate the exact same neurological response in people. These metamers have been substantially analyzed and demonstrate that while the visible program is skilled at using the sub tested details, the HVS can be fooled by certain spatial preparations of the stimulation.

There exist many examples of visible stimulating elements (and illusions) that expose the ways in which HVS accomplishes efficient handling. The metameric behavior that the HVS style displays has been utilized by technicians for picture and movie handling. The relatively greater understanding of the HVS to luminance details than chrominance (color) details has been utilized in the style of movie pressure methods, where more bits are allocated to each piece of luminance details (on average) than to corresponding pieces in the co-located shade programs. Different visible stimulating elements can stimulate the same percept when the visible program combines details from different hints to build effective understanding. Recent tests on cue conicts have shown that the visible program reports a particular scene parameter as a calculated regular of each cue and hence, multiple cue-conict stimulating elements can stimulate the same understanding.

While there has been significant interest in creatively lossless (VL) stress of medical image information, the area of general-purpose VL stress of movie segments has not been significantly examined. In this, a deep evaluation of the question of VL pressure of movie clips compacted using the H.264/AVC encoder is conducted. The results of the research are mathematically analyzed using mathematical methods and implications are made regarding of a routine of losslessness of pressure and its relationship to the material.

Substantial analysis has been devoted towards achieving better movie pressure via such diverse systems as spatial and temporary sub testing while development and learning centered interpolation schemes for decoding, to deliver appropriate stages of visible great quality at the recipient. When contracting healthcare pictures (for example, radiograms) it is imperative to be able to consistently retain all of the visible information that might be needed to create accurate determines. Such diagnostically lossless pressure for pictures has usually been analyzed in the perspective of the JPEG and JPEG2000 pressure standards, whereby customer analysis are performed and appropriate pressure bit-rates are decided based on analytic analysis. VL analysis are usually performed using an AFC, where topics are requested to view two pictures (one compressed and other un-compressed) and requested which of the two pictures they believed had better great quality.

JND research has been used to suggest JND styles for stress which assurance that the disruptions are not recognized. Such designs are defined in the DCT, wavelet or spatial domain and the designs have been used to design perceptually-optimal quantization matrices or to perform perceptually-relevant watermarking. Particularly, two JND designs have suggested recently for H.264/AVC conventional. The JND analysis and the VL analysis have a lot in typical, since both seek to define limits beyond which disturbances become imperceptible to the viewer. Yet while both are similar, these queries do not deal with the same issue and indeed may be considered as duals of each other.

The JND analysis require the topic to definitely check out the image/video for the presence of distortions, while the VL analysis simply ask the topic to rate which image/video s/he believed had better great quality. Since the customer is not definitely scanning for disturbances in the latter situation, one would hypothesize that VL limits may be greater (i.e., may allow for greater compression) than the JND limits. Further, picking the best great quality movie is usually an easier process than conducting an active check out for disturbances, since the customer may respond to non- pressure relevant flaws (e.g., lens aberration, movement jitter etc.) which can affect JND shapes. Much current analysis on lossless pressure has dealt with the pressure of pictures using JPEG/JPEG2000 encoders.

However, the areas of creatively lossless pressure of movie clips have seen only a limited perform, even in the healthcare industry. A 2-AFC process was developed in which bronchoscopy movie clips compacted over a variety of bit-rates using the H.264 codec were shown to topics along with the uncompressed original. In accordance with the customer ratings, the VL limit was found to be 172 Kbps for great movement movie but only 108 Kbps for the low movement one. Although the analysis consistently handled the issue of VL pressure of healthcare movie clips, outcomes of perform have a number of drawbacks which create video difficult to use the analysis outcomes to predict VL pressure stages in a typical video setting.

2.6. Summary and Motivation for the present Research

To summarize, numerous researchers have studied and developed various methods for the analysis JPEG2000 images and H.264 videos in NR method. However, further research is required to develop No-reference quality assessment techniques for the analysis of images and videos to meet the requirements of present high speed wireless data transfer systems to provide quality of image and video to end user without loss in the information. Hence, in the present thesis, the JPEG2000 images and H.264 videos are analyzed using No Reference Distortion Patch Features Image/Video Quality Assessment (NRDPF-IQA/VQA) based on Human Visual System and tested using the LIVE image/video database and Vignan University database. The overview of literature survey with methodology, drawbacks and future works are given in table 2.1.

Table 2.1: Overview of Literature survey with methodology, drawbacks and future works

Method	Year and Journal Name	Authors	Methodology	Drawbacks	Scope of Future works
CBIQ	2011, IEEE - ICIP	P. Ye and D. Doermann	visual codebook consisting of robust appearance	It does not assume any specific types of distortion	Distortion to be considered
LBIQ	2011 IEEE - ICCVPR	H. Tang, et al.,	low-level image features in a machine learning	Poor SROCC and LCC	Patch Features to be considered
DIIVINE	2011 IEEE TRANSACTIONS IP	A. K. Moorthy, et al.,	distortion-agnostic approach to blind IQA that utilizes concepts from NSS	utilizes a 2-stage framework	approach is modular, in that it can easily be extended beyond the pool of distortions
BLIINDS-II	2012 IEEE TRANSACTIONS IP	M. Saad, et al.,	DCT coefficients to perform distortion-agnostic NR IQA	avoid modeling poorly understood HVS	Based on Human Visual Systems
BRISQUE	2012 IEEE TRANSACTIONS IP	A. Mittal, et al.,	natural scene statistic (NSS)-based distortion without transformation	JPEG2000 distortion images correlation is poor compared with other distortions	orientations will be increased. HVS based IQA analysis.
Weighted Macro-Block Error Rate (WMBER)	2012 Proceedings SPIE	H. Boujut et al.,	merge the bottom-up saliency maps with the semantic saliency map	faces of large size will impact the metric	low weight on the semantic saliency map
Video-BLIINDS	2014 IEEE TRANSACTIONS IP	M. Saad, et al.,	spatio-temporal natural scene statistics	specific set of distortions and associated human scores	small number of computationally convenient features

Chapter-3

QUALITY ASSESSMENT OF JPEG2000 IMAGES BASED ON HUMAN VISUAL SYSTEM

3. QUALITY ASSESSMENT OF JPEG2000 IMAGES BASED ON HUMAN VISUAL SYSTEM

3.1. Introduction

Human observers can easily assess the quality of a distorted picture without examining the original picture as referrals. Currently, NR quality evaluation is feasible only when knowledge about the types of picture distortion is available. This research aims to develop NR quality statistic methods for JPEG2000 compressed pictures. First, it established JPEG2000 picture database which are taken from LIVE databases and very subjective tests were conducted on the database. The earlier BRISQUE design for no referrals picture quality evaluation, which is not consider the patch features of the picture, is a poor indicator of very subjective quality is studied. Therefore, tuning an NR statistic design towards BRISQUE is not an appropriate approach in developing NR quality metrics. Furthermore, a computational and memory efficient NR quality evaluation design for JPEG2000 pictures is proposed. Subjective test results are used to train the design, which achieves quality prediction performance.

In this chapter, a new approach to measure the quality of JPEG2000 pictures is presented. The functions for forecasting the perceived picture quality are extracted by considering key human visual system (HVS) factors such as contrast, qualifications activity and qualifications luminance. Picture quality assessment involves calculating the functional relationship between HVS functions and subjective test scores. The features of the compacted images are obtained without making reference to their unique images (‘No Reference’ metric). Here, the problem of quality evaluation is modified to a classification problem and fixed using No-Reference Distortion Patch Features Image Quality Assessment (NRDPF-IQA) criteria. The trial outcomes are compared with the existing JPEG2000 no-reference picture quality measurement and full-reference structural likeness picture quality measurement.

3.2. No Reference Distortion Patch Features Image Quality Analysis

The strategy for the NR IQA can be described as follows. Given a (possibly distorted) picture, first estimate regionally stabilized luminance via regional mean subtraction and divisive normalization (M.C.Q.Farias et al., 2005, Anish mittal et al., 2012, M.J.Chen et al., 2013). Much latest perform has targeted on modeling the research of reactions of organic pictures using multiscale converts (e.g., Gabor filtration, wavelets etc.). Given that neuronal reactions in place of visible cortex execute scale-space alignment decompositions of visible information, convert sector designs seem like organic techniques, particularly in perspective of the power compaction (sparsity) and decorrelating qualities of these converts when along with divisive normalization techniques. However, effective designs of spatial luminance research have also obtained interest from perspective scientists (Anish mittal et al., 2012).

3.2.1. Introduction to NRDPF-IQA Algorithm

The researches of organic pictures were analyzed in which the variations of grayish stage principles between one pixel and its nearby pixel (p) were regarded as the types. Derivatives between the sets of p can have six orientations: Horizontally (H), Vertical (V), Main-Diagonal (MD), Secondary-Diagonal (SD), Horizontal-Vertical (HV), and Combined-Diagonal (CD).

I(i-1 , j-1)	I(i-1 , j)	I(i-1 , j+1)
I(i , j-1)	I(i , j)	I(i , j+1)
I(i+1 , j-1)	I(i+1 , j)	I(i+1 , j+1)

Fig.3.1. Paired differences computed in order to quantify neighboring pixels

The following expressions represent the paired difference between the neighboring statistical relationship for six orientations at a distance of one pixel and edge pixel orientations. These are obtained from fig.3.1.

$$\mathrm{H}: \nabla_x \mathrm{I}(\mathrm{i},\mathrm{j}) = \mathrm{I}(\mathrm{i},\mathrm{j}+1) - \mathrm{I}(\mathrm{i},\mathrm{j}) \quad (3.2.1)$$

$$\mathrm{V}: \nabla_y \mathrm{I}(\mathrm{i},\mathrm{j}) = \mathrm{I}(\mathrm{i}+1,\mathrm{j}) - \mathrm{I}(\mathrm{i},\mathrm{j}) \quad (3.2.2)$$

$$\mathrm{MD}: \nabla_{xy} \mathrm{I}(\mathrm{i},\mathrm{j}) = \mathrm{I}(\mathrm{i}+1,\mathrm{j}+1) - \mathrm{I}(\mathrm{i},\mathrm{j}) \quad (3.2.3)$$

$$\mathrm{SD}: \nabla_{yx} \mathrm{I}(\mathrm{i},\mathrm{j}) = \mathrm{I}(\mathrm{i}+1,\mathrm{j}-1) - \mathrm{I}(\mathrm{i},\mathrm{j}) \quad (3.2.4)$$

$$\mathrm{HV}: \nabla_x \nabla_y \mathrm{I}(\mathrm{i},\mathrm{j}) = \mathrm{I}(\mathrm{i}-1,\mathrm{j}) + \mathrm{I}(\mathrm{i}+1,\mathrm{j}) - \mathrm{I}(\mathrm{i},\mathrm{j}-1) - \mathrm{I}(\mathrm{i},\mathrm{j}+1) \quad (3.2.5)$$

$$\mathrm{CD}_1: \nabla_{cx} \nabla_{cy} \mathrm{I}(\mathrm{i},\mathrm{j})_1 = \mathrm{I}(\mathrm{i},\mathrm{j}) + \mathrm{I}(\mathrm{i}+1,\mathrm{j}+1) - \mathrm{I}(\mathrm{i},\mathrm{j}+1) - \mathrm{I}(\mathrm{i}+1,\mathrm{j}) \quad (3.2.6)$$

$$\mathrm{CD}_2: \nabla_{cx} \nabla_{cy} \mathrm{I}(\mathrm{i},\mathrm{j})_2 = \mathrm{I}(\mathrm{i}-1,\mathrm{j}-1) + \mathrm{I}(\mathrm{i}+1,\mathrm{j}+1) - \mathrm{I}(\mathrm{i}-1,\mathrm{j}+1) - \mathrm{I}(\mathrm{i}+1,\mathrm{j}-1) \quad (3.2.7)$$

$$\mathrm{CD}_3: \nabla_{cx} \nabla_{cy} \mathrm{I}(\mathrm{i},\mathrm{j})_3 = \mathrm{I}(\mathrm{i},\mathrm{j}) + \mathrm{I}(\mathrm{i}+1,\mathrm{j}-1) - \mathrm{I}(\mathrm{i},\mathrm{j}-1) - \mathrm{I}(\mathrm{i}+1,\mathrm{j}) \quad (3.2.8)$$

$CD_4: \nabla_{cx}\nabla_{cy}I(i,j)_4 = I(i+1,j-1) + I(i-1,j+1) - I(i+1,j+1) - I(i-1,j-1)$ (3.2.9)

In accordance with the six orientations and the spatial place of pixel principles, it suggested nine kinds of expressions. Where I (i, j) symbolizes the pixel principles or coefficients corresponding to spatial place i, j.

The expression (3.2.1) to (3.2.4) and (3.2.6) are described on nearby pixels/pixel sets and equations (3.2.5) and (3.2.7) to (3.2.9) are described on a spot dimension 3X3.

To make new images/ picture sub groups J by considering the logarithm of each p value.

$J(i,j) = \log\,[I(i,j) + K]$ (3.2.10)

where K is a continuous that stops I(i , j) from being zero. Depending on expression (3.2.1) to (3.2.9), nine kinds of log-derivatives are determine as given

$D_1: \nabla_x J(i,j) = J(i,j+1) - J(i,j)$ (3.2.11)

$D_2: \nabla_y J(i,j) = J(i+1,j) - J(i,j)$ (3.2.12)

$D_3: \nabla_{xy} J(i,j) = J(i+1,j+1) - J(i,j)$ (3.2.13)

$D_4: \nabla_{yx} J(i,j) = J(i+1,j-1) - J(i,j)$ (3.2.14)

$D_5: \nabla_x\nabla_y = J(i-1,j) + J(i+1,j) - J(i,j-1) - J(i,j+1)$ (3.2.15)

$D_6: \nabla_{cx}\nabla_{cy}J(i,j)_1 = J(i,j) + J(i+1,j+1) - J(i,j+1) - J(i+1,j)$ (3.2.16)

$D_7: \nabla_{cx}\nabla_{cy}J(i,j)_2 = J(i-1,j-1) + J(i+1,j+1) - J(i-1,j+1) - J(i+1,j-1)$ (3.2.17)

$D_8: \nabla_{cx}\nabla_{cy}J(i,j)_3 = J(i-1,j-1) + J(i+1,j+1) - J(i-1,j+1) - J(i+1,j-1)$ (3.2.18)

$D_9: \nabla_{cx}\nabla_{cy}J(i,j)_4 = J(i+1,j-1) + J(i-1,j+1) - J(i+1,j+1) - J(i-1,j-1)$ (3.2.19)

The recognizable quality of a picture can be affected by the mathematical information engaged in both the spatial and regularity. The suggested No Reference Distortion Patch Features includes spatial sector features.

The functions produced in the spatial sector include two types:

(1) Pointwise differences based statistics for single pixel values and

(2) Pairwise differences based log derivative statistics for the relationship of pixel pairs.

Particularly, an picture I (i , j), first estimate regionally stabilized pixel principles via regional mean subtraction and divisive normalization described as

$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}$ (3.2.20)

where

$i \in \{1, 2, \ldots, M\}$ and $j \in \{1, 2, \ldots, N\}$ are spatial indices.

M = image height

N = image width

C = 1 is a constant that prevents division by zero

The amounts $\mu(i, j)$ and $\sigma(i, j)$ are described as

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}\ I_{k,l}I(i,j) \tag{3.2.21}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}\left(I_{k,l}I(i,j) - \mu(i,j)\right)^2} \tag{3.2.22}$$

calculate the regional mean $\mu(i, j)$ and comparison $\sigma(i, j)$.

where $\omega = \{\omega_{k,l} \setminus k=-K, \ldots, K, l=-L, \ldots, L\}$ is a 2D circularly–symmetric Gaussian weighting operate tested out to 3 conventional diversions (K=L=3) and rescaled to device quantity.

A GGD (Generalized Gaussian Distribution model) distortion is used as a design of the scientific distortions of the MSCN (Mean Subtracted Contrast Normalized) coefficients of organic pictures and how they modify with distortions. The GGD with zero mean is given by

$$f(x;\alpha,\sigma^2) = \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)}\exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{3.2.23}$$

where

$$\beta = \alpha\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \tag{3.2.24}$$

The parameter α manages the common form of the submission and σ manages the difference.

$$\Gamma(a) = \int_0^{\infty} t^{a-1}\ e^{-t}dt \quad a>0 \tag{3.2.25}$$

$\Gamma(.)$ is the gamma function. The factors of the GGD (α , $\sigma2$) can be effectively approximated using when related based strategy.

The present features of NRDPF-IQA are given by analyzing the distribution of the differences of the places of close by coefficients measured along Horizontal (H), Vertical (V), and Diagonal (D) orientations. The item of nearby coefficients is well made as following a zero method Asymmetric General Gaussian Distribution (AGGD).

$$f(x;\alpha,\sigma_l^2,\sigma_r^2) = \begin{cases} \frac{\alpha}{\beta_l+\beta_r\Gamma\left(\frac{1}{\alpha}\right)}\exp\left(-\left(\frac{-x}{\beta_l}\right)^{\alpha}\right) & x<0 \\ \frac{\alpha}{\beta_l+\beta_r\Gamma\left(\frac{1}{\alpha}\right)}\exp\left(-\left(\frac{x}{\beta_r}\right)^{\alpha}\right) & x\geq 0 \end{cases} \tag{3.2.26}$$

where

$$\beta_l = \sigma_l \sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \tag{3.2.27}$$

$$\beta_r = \sigma_r \sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \tag{3.2.28}$$

The factors of the AGGD (α, σ_l^2, σ_r^2) can be effectively approximated using when related centered strategy. Mean of the submission is used as a function as given in equation (3.2.29).

$$\eta = (\beta_r - \beta_l) \frac{\Gamma\left(\frac{2}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)} \tag{3.2.29}$$

Under the Gaussian coefficients design and supposing the MSCN coefficients are zero mean and device difference. These items follow the following submission in the lack of distortions as given in equation (3.2.30).

$$f(x, \rho) = \frac{\exp\left(\frac{|x|\rho}{1-\rho^2}\right) K_0\left(\frac{|x|}{1-\rho^2}\right)}{\Pi\sqrt{(1-\rho^2)}} \tag{3.2.30}$$

where

f is an asymmetric probability density function,

$\boldsymbol{\rho}$ denotes the correlation coefficient of adjacent coefficient,

K_0 is the modified Bessel function of the second kind.

36 factors are calculated at two machines to catch multiscale actions, by low pass filtration and down testing by a factor of 2, producing a set of 36 functions.

3.2.2. Implementation of NRDPF-IQA Algorithm

The NRDPF-IQA model is used to estimate the 36 identical no reference distortion patch features from areas of the same size PXP from the picture to be quality examined, suitable then with the Multivariate Gaussian Design. The altered picture is indicated as the distance between the features functions model and Multivariate Gaussian Design to fit the functions produced from altered picture.

$$D(\propto_1, \propto_2, \sigma_1^2, \sigma_2^2) = \sqrt{((\propto_1 - \propto_2)^T((\sigma_1^2 + \sigma_2^2)/2)^{-1}(\propto_1 - \propto_2))} \tag{3.2.31}$$

where α_1, α_2, σ_1^2, σ_2^2 are the mean and covariance of the Multivariate Gaussian Model.

The equations from (3.2.1) to (3.2.19) signify the features of the distortions areas. It also noticed that the stabilized luminance principles highly seem towards a device regular Gaussian attribute for pictures.

The above equations from (3.2.20) to (3.2.30) are used to create the MATLAB program to get the picture quality ranking. The following is the block diagram of NRDPF-IQA algorithm shown in fig.3.2.

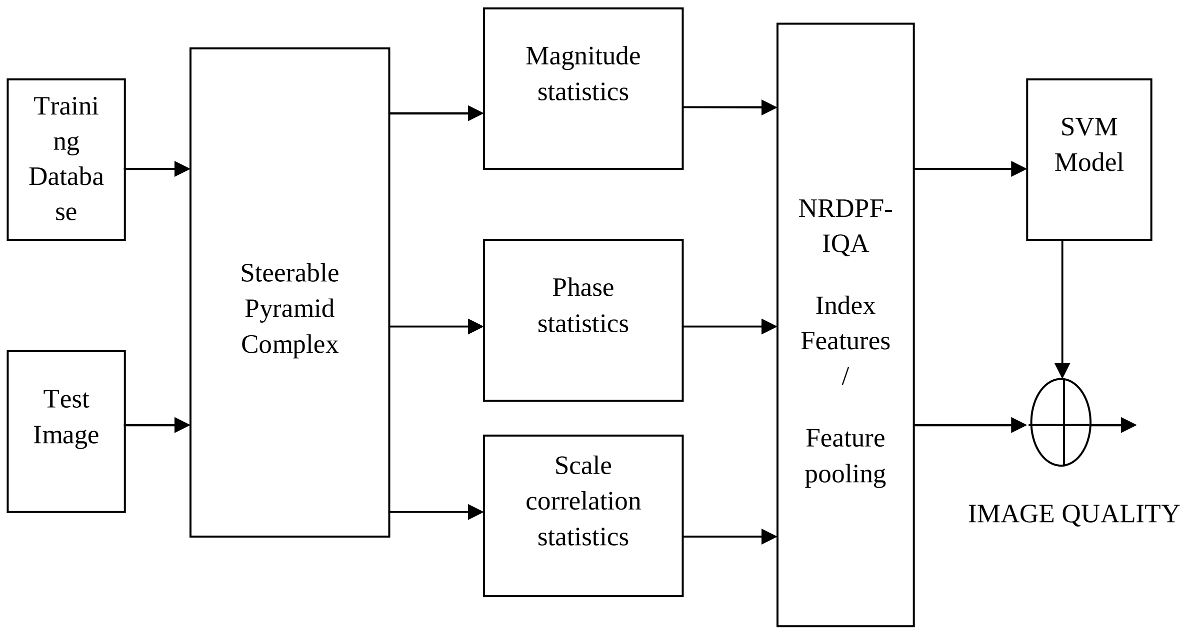

Fig.3.2. Image quality assessment using NRDPF-IQA algorithm

NRDPF-IQA Procedure:

Step1. Stabilize the Input image into 768*512 sizes from database.

Step2. Turn the picture into perfection principles.

Step3. Reshape the image into information places of line vector for segmentation.

Step4. Determine the number of clusters i.e. centroids.

Step5. Determine the range between input information set factors and set factors of the centroids.

Step6. Find the information set factors which are nearby to the centroid.

Step7. Choose the centroid with lowest range then shift the dataset factors to the nearest appropriate centroids

Step8. Re calculate the centroids by choosing the highest possible pixel value from the set of appropriate centroid information factors.

Step9. Do it again until the new centroids and the previous centroids are shaped.

Step10. Spend the account principles -1, 0 and 1 to each pixel of the group centroids

Step11. Estimate the global threshold value T.

Step12. Figure out the information set factors with identical account value and then change the new marking.

Step13. Implement the binary choice to acquire the resulting marking of picture.

Step14. Consider 768*512 Image as a single region and represent it as ‘ I’.

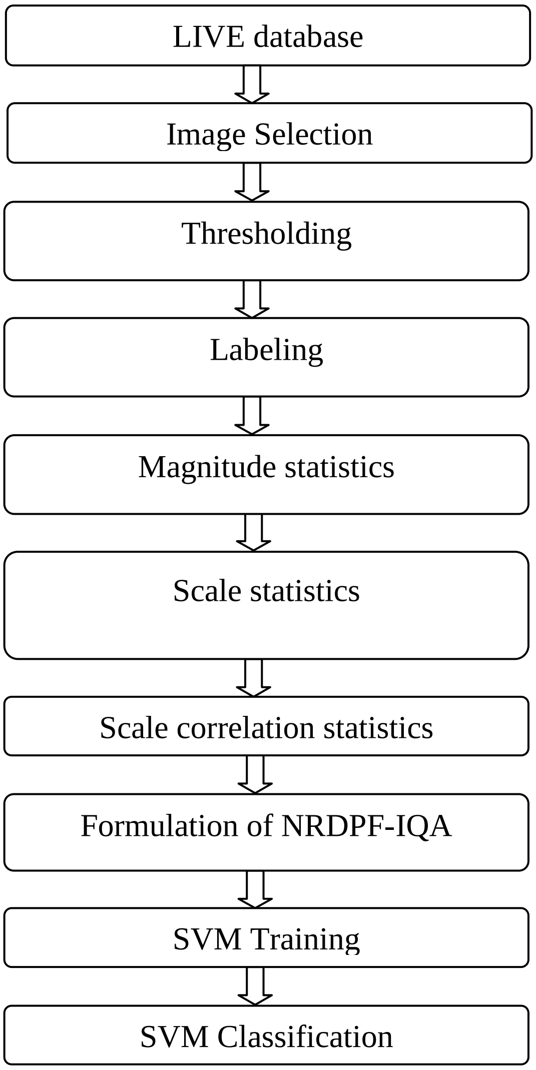

Fig.3.3. Testing of NRDPF-IQA method for image quality assessment

The above prevent plan shows that the process for use of the NRDPF-IQA criteria in picture quality assessment. Lastly, SVM training and examining is done for the criteria. The process is shown in fig.3.3.

3.3 Performance Analysis of No Reference Image Quality

The ultimate phase is to map the function vectors to calculate of picture quality. L-moments are useful for calculating the factors of submission. The estimators are relatively unchanged by small departures from design supposition.

3.3.1 Introduction

The L-moments of a sample $X_{(i)}$, i=1, 2, … , N utilize probability weighted moments of the order statistics $X_{(i)}$, i=1, 2, … , N of the sample.

$$b_0 = \frac{\sum_{i=1}^{N} X_{(i)}}{N} \tag{3.3.1}$$

$$b_r = \frac{\sum_{i=r+1}^{N} \frac{(i-1)(i-2)\ldots.(i-r)}{(n-1)(n-2)\ldots.(n-r)} X_{(i)}}{N} \tag{3.3.2}$$

The L-moments are then indicated as straight line mixtures of the possibility calculated minutes.

$$l_1 = b_0 \tag{3.3.3}$$

$$l_2 = 2b_1 - b_0 \tag{3.3.4}$$

$$l_3 = 6b_2 - 6b_1 + b_0 \tag{3.3.5}$$

$$l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \tag{3.3.6}$$

The No Referrals Distortions Spot Functions using L-moment based research are carefully related to L-estimators substantially used in picture filtration concept. The second and fourth L-moments are calculated from the point sensible research of MSCN coefficients corresponding to (σ^2, α). Good and bad L-moments are managed independently since the AGGD design is generally asymmetric. This process is conducted in No Reference Distortion Patch Features Image Quality Assessment.

LIVE IQA database is used to analyze the efficiency of NRDPF-IQA criteria, which made up of 982 pictures in different groups like JPEG2000, JPEG, white-colored Gaussian noise (WN), Gaussian Blur, a Rayleigh Fast-Fading. Each of the distortions pictures has an associated distinction DMOSS. This symbolizes the very subjective quality picture. Since NRDPF-IQA strategy needs a coaching process to adjust the regressor component, the LIVE database split into two arbitrarily selected subsets – 80% training and 20% testing – such that no overlap between train and test. The revealed results do not rely on features produced from known material, which can synthetically improve efficiency shown in table 3.1. Further, this unique analyze process 1000 times and review the average of the efficiency across these 1000 versions, in order to remove efficiency prejudice.

Table 3.1: Median Spearman Rank Ordered Correlation Coefficient (SROCC) across 1000 Train-Test combinations on the LIVE IQA database for all types of distortions. Bold Indicate JPEG2000 compressed image database.

Method	Type of Distortion					
	JPEG2000	JPEG	WN	Blur	FF	ALL
PSNR	**0.8646**	0.8831	0.9410	0.7515	0.8736	0.8636
SSIM	**0.9389**	0.9466	0.9635	0.9046	0.9393	0.9129
MS-SSIM	**0.9627**	0.9785	0.9773	0.9542	0.9386	0.9535
CBIQ	**0.8935**	0.9418	0.9582	0.9324	0.8727	0.8954
LBIQ	**0.9040**	0.9291	0.9702	0.8983	0.8222	0.9063
BLIINDS-II	**0.9323**	0.9331	0.9463	0.8912	0.8519	0.9124
DIIVINE	**0.9123**	0.9208	0.9818	0.9373	0.8694	0.9250
Pointwise	**0.7957**	0.8593	0.9608	0.8759	0.7773	0.8297
Pairwise	**0.9007**	0.9510	0.9773	0.8759	0.8741	0.9302
BRISQUE	**0.9139**	0.9647	0.9786	0.9511	0.8768	0.9395
NRDPF-IQA (Proposed)	**0.9886**	0.9814	0.9863	0.9612	0.9462	0.9585

The spatial strategy to NR IQA that can be described as follows, given a (possibly distorted) picture, first estimate regionally stabilized luminances via regional mean subtraction and divisive normalization. Ruderman noticed that implementing a regional non-linear function to log-contrast luminances to eliminate regional mean displacements from zero log-contrast and to stabilize the regional difference of the log-contrast has a decorrelating impact. Ruder man also noticed that these stabilized luminance principles highly seem towards a unit normal Gaussian attribute for natural pictures.

Such function can be used to design the contrast-gain covering up process in early human perspective. It implement the pre-processing design in this QA design growth and make reference to the modified luminances as mean subtracted contrast normalized (MSCN) coefficients. There is high connection between around p because picture features are generally piecewise sleek aside from rare advantage discontinuities. The normalization process significantly decreases dependencies between nearby coefficients as is obvious in the plots proven in the right line. To be able to help people imagine what the non-linear modification does to picture, the difference area features item limitations and other regional high comparison trend. The MSCN area, the features are not clearly decorrelated, displays a mostly homogeneous overall look with a few low-energy recurring item limitations.

The speculation is that the MSCN coefficients have attribute mathematical qualities that are modified by the existence of distortions, and that quantifying these changes will make it possible to estimate the type of distortions impacting picture as well as its perceptual quality. To be able to imagine how the MSCN coefficient withdrawals differ as operate of distortions, Observe how the referrals picture displays a Gaussian like overall look, as noticed by Ruder man, while each distortions adjusts the research in its own attribute way.

Table 3.2: Median Linear Correlation Coefficient across 1000 Train-Test combinations on the LIVE IQA database for all types of distortions. Bold Indicate JPEG2000 compressed image database.

Method	Type of Distortion					
	JPEG2000	JPEG	WN	Blur	FF	ALL
PSNR	**0.8762**	0.9029	0.9173	0.7801	0.8795	0.8592
SSIM	**0.9405**	0.9462	0.9824	0.9004	0.9514	0.9066
MS-SSIM	**0.9746**	0.9793	0.9883	0.9645	0.9488	0.9511
CBIQ	**0.8898**	0.9454	0.9533	0.9338	0.8951	0.8955
LBIQ	**0.9103**	0.9345	0.9761	0.9104	0.8382	0.9087
BLIINDS-II	**0.9386**	0.9426	0.9635	0.8994	0.8790	0.9164
DIIVINE	**0.9233**	0.9347	0.9867	0.9370	0.8916	0.9270
Pointwise	**0.7947**	0.8447	0.9711	0.8670	0.8151	0.8258
Pairwise	**0.8968**	0.9571	0.9830	0.8670	0.8952	0.9309
BRISQUE	**0.9229**	0.9734	0.9851	0.9506	0.9030	0.9424
NRDPF-IQA (Proposed)	**0.9898**	0.9805	0.9868	0.9714	0.9612	0.9546

Cloud makes a more Laplacian overall look, while a white-noise distortion seems to decrease the weight of the end of the histogram. A General Gaussian Distribution (GGD) can be used to successfully catch a wider variety of altered picture research, which often display changes in the end behavior (i.e. kurtosis) of the scientific coefficient withdrawals where the GGD with zero mean is given by: The form parameter α manages the 'shape' of the submission while σ2 management the difference. It selects the zero mean submission, since (generally) MSCN coefficient withdrawals are symmetrical. The factors of the GGD (α, σ^2), are approximated using the moment-matching centered strategy suggested. The results are shown in table 3.2.

This parametric design to fit the MSCN scientific withdrawals from altered pictures as well as undistorted ones is formed. For each picture, calculate 2 factors (α, σ^2) from a GGD fit of the MSCN coefficients. These type the first set of functions that will be used to catch picture disturbances. To demonstrate that breathtaking and altered pictures are well divided in GGD parameter area, a set of breathtaking pictures are taken from the Berkeley picture segmentation data source. Identical types of disturbances as existing in the LIVE IQA data source - JPEG2000, JPEG, white-noise, Gaussian cloud, and quick diminishing route mistakes were presented in each picture at different levels of intensity to type the altered picture set.

White-colored disturbance is very clearly divided from the breathtaking picture set making it one of the most convenient to evaluate the quality of JPEG2000 and quick diminishing have a high level of overlap as quick diminishing pictures in LIVE database are actually multidistorted, first compacted into a bit stream using a JPEG2000, then approved through a Rayleigh quick diminishing route to imitate bundle loss. The mathematical connections between nearby p are designed. While MSCN coefficients are definitely more homogenous for breathtaking pictures, symptoms and symptoms of nearby coefficients also display a frequent framework, which gets disrupted in the existence of disturbances. The framework using the scientific withdrawals of pair wise items of nearby MSCN coefficients along six orientations are designed.

Under the Gaussian coefficient design and supposing the MSCN coefficients are zero mean and device difference, these items follow the following submission in the lack of disturbances. The MSCN coefficients for JPEG2000 are shown in fig. 3.4. Where f is asymmetric possibility solidity operate, ρ signifies the connection coefficient of nearby coefficients, and K_0 is the customized Bessel operate of the second type. Differ in the existence of distortions, the histograms of combined items along each of six orientations, for a referrals picture and for altered editions of it the type parameter ν controls the 'shape' of the distribution while σ_l^2 and σ_r^2 are variety aspects that management the spread on each part of the technique, respectively. The AGGD further generalizes the common Gaussian Distribution (GGD) and subsumes it by allowing for asymmetry in the distribution. Modify of the distribution is a function of the staying and right variety aspects. If $\sigma_l^2 = \sigma_r^2$, then the AGGD decreases to the GGD. Although the AGGD is rarely used, it has been implemented to design manipulated heavy-tailed withdrawals of picture framework.

The factors of the AGGD (ν, σ_l^2, σ_r^2), are approximated using the moment-matching based strategy suggested. It can be imagined that different disturbances take up different areas of the area. Also, pictures are anticipated to have a better separating when made in the high perspective area of factors acquired by suitable AGGD withdrawals to combined items from different orientations and machines together. Images are normally multiscale, and disturbances impact picture framework across machines. Further, as research in quality evaluation has confirmed, integrating multiscale details when evaluating quality generates QA methods that perform better with regards to connection with individual understanding.

Hence, all functions detailed at two ways - the unique picture range, and at a decreased quality (low successfully pass strained and down sampled by an aspect of 2). Thus, a finish of 36 features – 18 at each variety, is used to identify disruptions and to perform distortion-specific quality evaluation. The SROCC between each of these functions and individual DMOS from the LIVE IQA database, for each of the disturbances in the database – JPEG and JPEG2000 compression, additive white Gaussian noise, Gaussian cloud and a Rayleigh fast fading, to determine how well the functions link with individual decision of quality.

Observe that no training is performed here; the story is simply to demonstrate that each function catches quality details and to demonstrate that pictures are impacted in a different way by different disturbances.

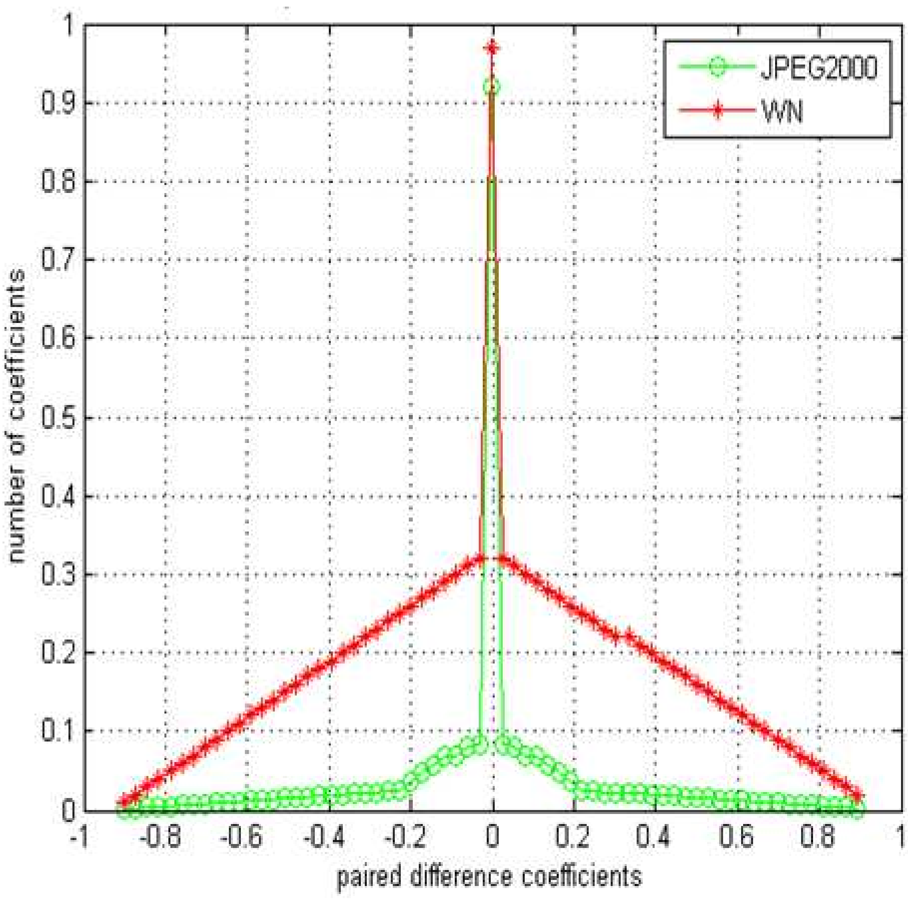

Fig.3.4. Paired difference of MSCN coefficients

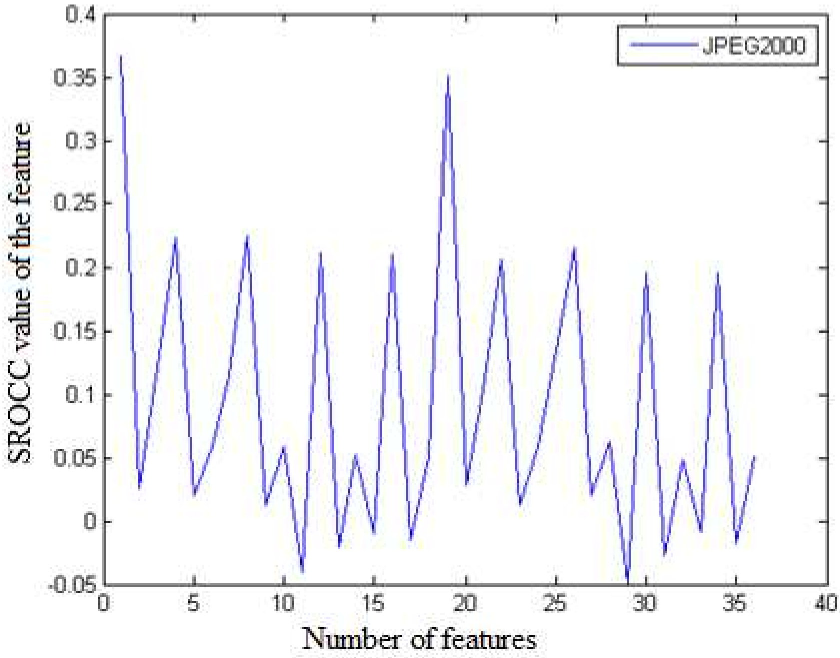

Fig.3.5. Image quality index performance for JPEG2000

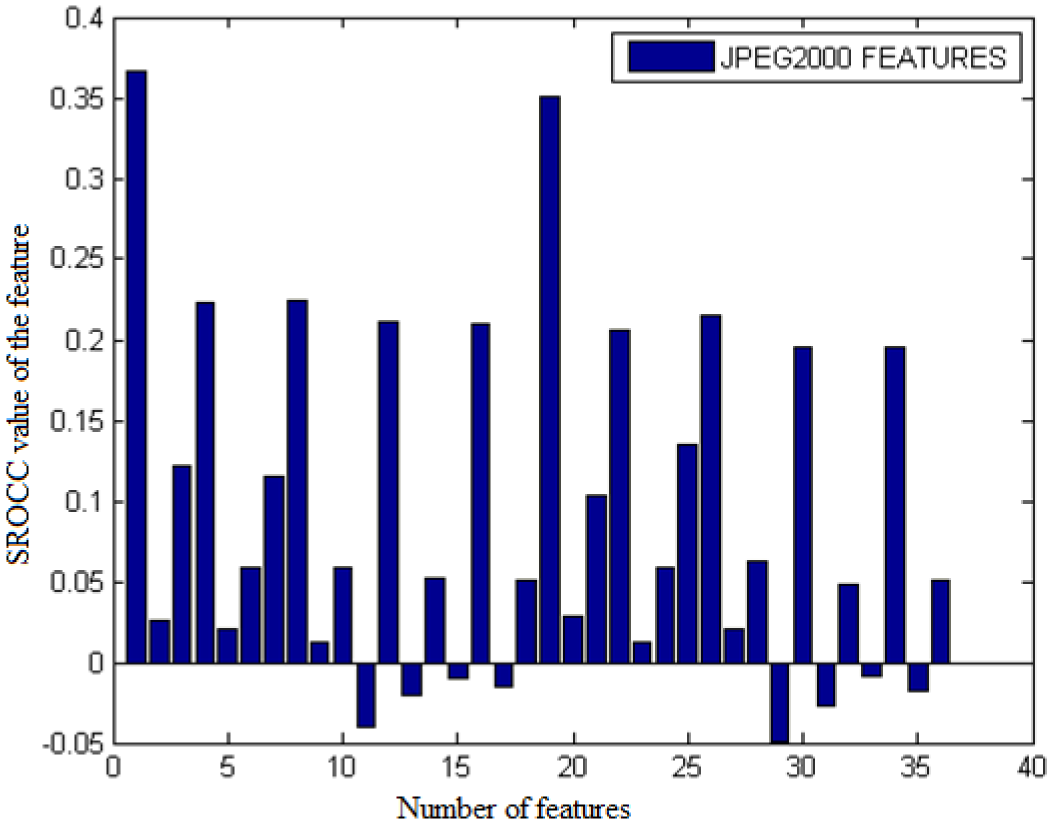

Fig.3.6. Image quality index features performance for JPEG2000

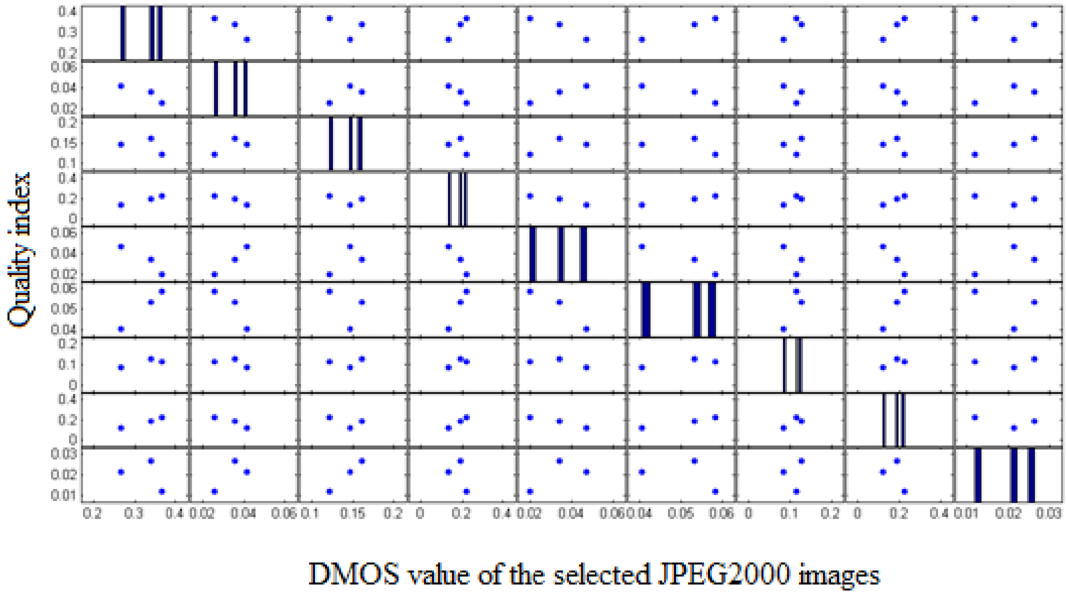

Fig.3.7. DMOS image quality index performance for JPEG2000

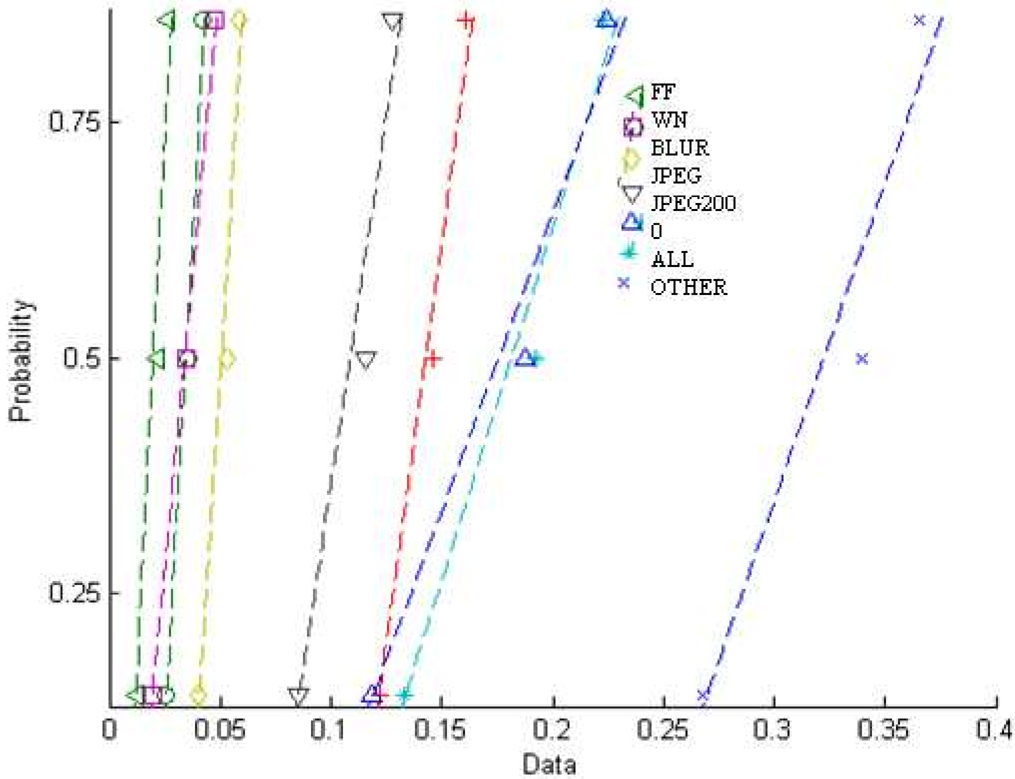

Fig.3.8. Probability based image quality representation

3.3.2. LIVE IQA database

LIVE IQA database is used to analyze the efficiency of NRDPF-IQA, which includes 29 referrals pictures with 982 altered pictures comprising five different distortions groups – JPEG2000 (JP2K) and JPEG compression, preservative white Gaussian noise (WN), Gaussian cloud (Blur), and a Rayleigh fast-fading (FF). Each of the altered pictures has an associated distinction mean viewpoint ranking which symbolizes the very subjective quality of the picture. Since the NRDPF-IQA strategy needs a coaching process to adjust the regressor component, the LIVE database is split into two arbitrarily selected subsets – 80% training and 20% testing – such that no overlap between practice and analyze. The revealed outcomes do not rely on functions produced from known spatial material, which can artificially enhance efficiency. Further, this unique train-test process 1000 times and review the average of the efficiency across these 1000 versions, to be able to remove efficiency prejudice. The Spearman’s rank ordered correlation coefficient (SROCC) and Pearson’s (linear) correlation coefficient (LCC) between the expected ranking from the criteria and DMOS were used to accessibility QA efficiency. Before processing LCC, the criteria ratings were approved through a logistic nonlinearity as described. A value near to 1 for SROCC and LCC indicate good efficiency with regards to connection with individual viewpoint. The results are compared with other methods as shown in table 3.3.

The efficiency of three full-reference indices: peak-signal-to-noise ratio (PSNR), SSIM and MS-SSIM are tabulated. Although PSNR is a bad evaluate of perceptual quality, it is often used to standard for QA methods. The SSIM and MS-SSIM spiders are popular due to their efficiency and convenience. The efficiency of the no-reference methods - CBIQ, LBIQ, BLIINDS-II and DIIVINE are tabulated. The efficiency of NRDPF-IQA continues to be relatively constant with regard to variation in of the size used to estimate the regional mean and differences.

Table 3.3: One sided t-test performed between SROCC values of various IQA algorithms. A value of "1" indicates that the row algorithm is statistically superior to the column algorithm; "-1" indicates that the row is worse than the column; a value "0" indicates two algorithms are statistically indistinguishable.

Method	Method								
	PSNR	SSIM	MS-SSIM	CBIQ	LBIQ	BLINDS-II	DIIVINE	BRISQUE	**NRDPF-IQA (Proposed)**
PSNR	**0**	**-1**	**-1**	**-1**	**-1**	**1**	**-1**	**-1**	**-1**
SSIM	**1**	**0**	**-1**	**1**	**1**	**1**	**1**	**-1**	**-1**
MS-SSIM	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**
CBIQ	**1**	**-1**	**-1**	**0**	**-1**	**1**	**-1**	**-1**	**-1**
LBIQ	**1**	**-1**	**-1**	**1**	**0**	**1**	**-1**	**-1**	**-1**
BLIINDS-II	**1**	**-1**	**-1**	**1**	**1**	**0**	**-1**	**-1**	**-1**
DIIVINE	**1**	**1**	**-1**	**1**	**1**	**1**	**0**	**-1**	**-1**
BRISQUE	**1**	**1**	**-1**	**1**	**1**	**1**	**1**	**0**	**-1**
NRDPF-IQA (Proposed)	**1**	**1**	**-1**	**1**	**1**	**1**	**1**	**1**	**0**

3.3.3. Comparison with existing Algorithms

The structure is general enough to allow for the use of any regressor. In this execution, support vector machine (SVM) regressor (SVR) is used. SVR has formerly been used to picture quality evaluation problems. For example, a studying motivated operates combining strategy using SVR was suggested. Wavelet-domain NSS and unique value breaking down functions have been used to map quality to human scores via SVR. SVR is usually mentioned for being able to deal with high perspective information. The LIBSVM program is used to apply the SVR with a radial foundation operate kernel.

Determine the mean SROCC across the 1000 tests and the conventional diversions of efficiency across these 1000 tests for each of the methods regarded here. Although there are available variations in the average connections between the different methods, these variations may not be mathematically appropriate. Hence, to assess the mathematical importance of efficiency of each of the methods regarded, speculation examining in accordance with the t-test on the SROCC principles acquired from the 1000 train-test tests is conducted. The results are shown in fig.3.5. The zero speculation is that the mean connection for the (row) criteria is similar to mean connection for the (column) criteria with an assurance of 95%. The different speculation is that the mean connection of row is higher than or smaller than the mean connection of the line. A value of '1' in the table indicates that the row criterion is statically excellent to the line criteria, whereas a '−1' indicates that the row is mathematically more intense than the line. A value of '0' indicates that the row and line are mathematically indistinguishable (or equivalent), i.e., it could not decline the zero speculation at the 95% level of assurance. The results are shown in table 3.3. NRDPF-IQA is extremely aggressive with all no reference methods examined and mathematically better than the full reference methods PSNR and SSIM. Given that these actions need more information through the referrals picture, this is certainly not a small accomplishment. This outcome indicates that to the level disturbances can be qualified on; one can substitute full reference methods such as SSIM with the suggested NRDPF-IQA without any loss of efficiency. The results are shown in fig.3.6. NRDPF-IQA continues to be a little bit substandard to the FR MS-SSIM, showing that there may still be some space for enhancement in efficiency.

To be able to show that NRDPF-IQA functions are used for precise distortion-identification, the average category precision of the classifier for each of the disturbances in the LIVE database, as well as across all disturbances. The results are shown in fig.3.7. Further, to be able to imagine which disturbances are 'confused' the most, the misunderstandings matrix for each of the disturbances, where the sum of each row in the misunderstandings matrix is 1 and real principles signify the mean misunderstandings amount across the 1000 train-test tests. The results are shown in table 3.4. JP2K and JPEG are also puzzled sometimes. WN and Cloud are usually not puzzled with other disturbances. The results are shown in fig.3.8.

The chance of changing the one level structure, where functions are straight planned to quality, with a two-stage structure, just like that suggested. In this strategy, the same places of functions are used to recognize the distortions affecting the picture as are then used for distortion-specific QA. Such a two-stage strategy was used with latest achievements for NSS-based sightless IQA. The average SROCC value across 1000 tests for the two-stage understanding of NRDPF-IQA is tabulated. The activities of NRDPF-IQA are recorded for evaluation reasons. The efficiency can be linked to partial distortions recognition in the first level of the two-stage structure. The results are shown in table 3.5.

Table 3.4: Mean and median classification accuracy across 1000 train-test trails using NRDPF-IQA that the two algorithms are statistically indistinguishable.

Classification Accuracy (%)	Type of Distortion					
	JPEG2000	JPEG	WN	Blur	FF	ALL
MEAN	94.82	93.12	100.00	96.24	91.36	94.04
MEDIAN	**95.12**	**94.38**	**100.00**	**97.12**	**92.12**	**94.12**

Table 3.5: Median Spearman Rank Ordered Correlation Coefficient (SROCC) across 1000 Train-Test combinations on the LIVE IQA database. Bold Indicate proposed algorithm

Method	Type of Distortion					
	JPEG2000	JPEG	WN	Blur	FF	ALL
NRDPF-IQA (Proposed)	**0.9886**	**0.9814**	**0.9863**	**0.9612**	**0.9462**	**0.9585**

Having analyzed NRDPF-IQA on the LIVE IQA database, the efficiency of NRDPF-IQA is not limited by the database on which it is examined. The TID database includes 25 referrals pictures and 1700 altered pictures over 17 disturbances groups. Since there are only 24 organic pictures, and this criterion is in accordance with the research of organic pictures, the strategy only on these 24 pictures. The results are shown in table 3.6. Further, although there are available 17 disturbances groups, NRDPF-IQA only on these disturbances are examined that it is qualified for: JPEG, JPEG2000 compression (JP2K), preservative white-noise (WN) and Gaussian Cloud (blur) – FF disturbances does not are available in the TID database. The efficiency of PSNR and SSIM for evaluation reasons recorded. It should be obvious that NRDPF-IQA works well with regards to connection with individual understanding of quality and that the efficiency does not rely on the database.

NRDPF-IQA targeted on the relationship of the mathematical functions to natural field research and the effect that disturbances have on such research. However, given the few of functions that are produced (18 per scale) and the point that parameter evaluation needs to be conducted only 5 times for an entire picture, in evaluation to parameter evaluation for each prevent as in BLIINDS-II, people will appreciate the point that NRDPF-IQA is extremely efficient. Having confirmed that NRDPF-IQA works well in terms of connection with human understanding, NRDPF-IQA has low complexness.

To compare the overall computational complexness of NRDPF-IQA with the FR PSNR and the NR BLIINDS-II and DIIVINE, time taken (in seconds) to estimate each quality evaluate on an picture of quality 512×768 on a 1.8 GHz single-core PC with 2 GB of RAM recorded. Unoptimized MATLAB code is used for all of these methods to ensure a reasonable evaluation. The results are shown in table 3.7 and table 3.8. The performance as a portion of time taken to estimate PSNR is recorded, to allow for a machine-independent evaluation across methods. NRDPF-IQA is quite efficient, outperforming the DIIVINE catalog and the BLIINDS-II catalog by a great amount. This indicates that the spatial-domain NRDPF-IQA an ideal applicant for real-time sightless evaluation of visible quality.

3.3.4. Results and Discussions

LIVE IQA database is used to analyze the efficiency of NRDPF-IQA criteria. Since NRDPF-IQA strategy needs a coaching process to adjust the regressor component, the LIVE database is divided into two arbitrarily selected subsets – 80% training and 20% testing – such that no overlap between train and test. The results are shown in fig.3.8. The revealed results do not rely on features produced from known material, which can synthetically improve efficiency. Further, this unique analyze process 1000 times and review the average of the efficiency across these 1000 versions, in order to remove efficiency prejudice.

Although sightless strategy and the FR techniques do not need this process, to make sure a reasonable evaluation across techniques, the connections of expected ratings with individual decision of visible quality are only revealed on the analyze set. The dataset was separated into 80% training and 20% testing – getting good care that no overlap happens between practices and analyze material. This train-test process was recurring 1000 periods to make sure that there was no prejudice due to the spatial material used for coaching. The results are shown in fig.3.9. The average efficiency across all versions are recorded. Spearman's rank ordered correlation coefficient (SROCC), and Pearson's (linear) correlation coefficient (LCC) are used to analyze the design. The NRDPF-IQA ratings are approved through a logistic non-linearity before processing LCC for applying to DMOS area.

NRDPF-IQA is compared with three FR indices: PSNR, SSIM and multiscale SSIM (MS-SSIM), five common techniques - CBIQ, LBIQ, BLIINDS-II, DIIVINE and BRISQUE. NRDPF-IQA works better than the FR PSNR and SSIM and plays well with all of the executing NR IQA techniques. The results are shown in fig.3.10, fig.3.11 and fig.3.12. This is a pretty amazing business presentation of the connection between quantified picture naturalness and perceptual picture quality.

A support vector machine regressor (SVR) was used to learn a applying from function space to quality ratings where two different regressors were qualified using design centered and effective functions respectively. SVRs formerly have been used with success for picture quality evaluation. The LIBSVM program is used to apply the SVR; the RBF kernel was used for regression. Finally, JPEG2000 images are having good SROCC, LCC values in all databases. So, it concludes that NRDPF-IQA method is well suitable for the assessment of JPEG2000 images based on Human Visual System. The Median Spearman Rank Ordered Correlation Coefficient (SROCC) across 1000 train-test combinations on the LIVE-IQA database for different window sizes are shown in table 3.9.

Table 3.6: Spearman's Rank Order Correlation Coefficient (SROCC) on The TID2008 database. Bold Indicate NR-IQA algorithms and others are FR-IQA algorithm

Method	Type of Distortion				
	JPEG2000	JPEG	WN	Blur	ALL
PSNR	0.825	0.876	0.918	0.934	0870
SSIM	0.963	0.935	0.817	0.960	0.902
BRISQUE	**0.832**	**0.924**	**0.829**	**0.881**	**0.896**
NRDPF-IQA (Proposed)	**0.974**	**0.942**	**0.921**	**0.973**	**0.921**

Table 3.7: Informal complexity analysis of NRDPF-IQA. Tabulated values reflect the percentage of time devoted to each of the steps of NRDPF-IQA.

STEP	PERCENTAGE OF TIME
MSCN	48.7
GGD	8.1
Pair wise difference and AGGD	36.4

Table 3.8: Complexity analysis of NRDPF-IQA: a comparison of the amount of time taken to compute various quality measures for a 512x768 image on a 2.8GHZ intel core i3 PC with 4GB RAM.

ALGORITHM	TIME(SECONDS)
PSNR	0.05
DIIVINE	104.12
BLIINDS-II	35.12
BRISQUE	1.81
NRDPF-IQA	1.24

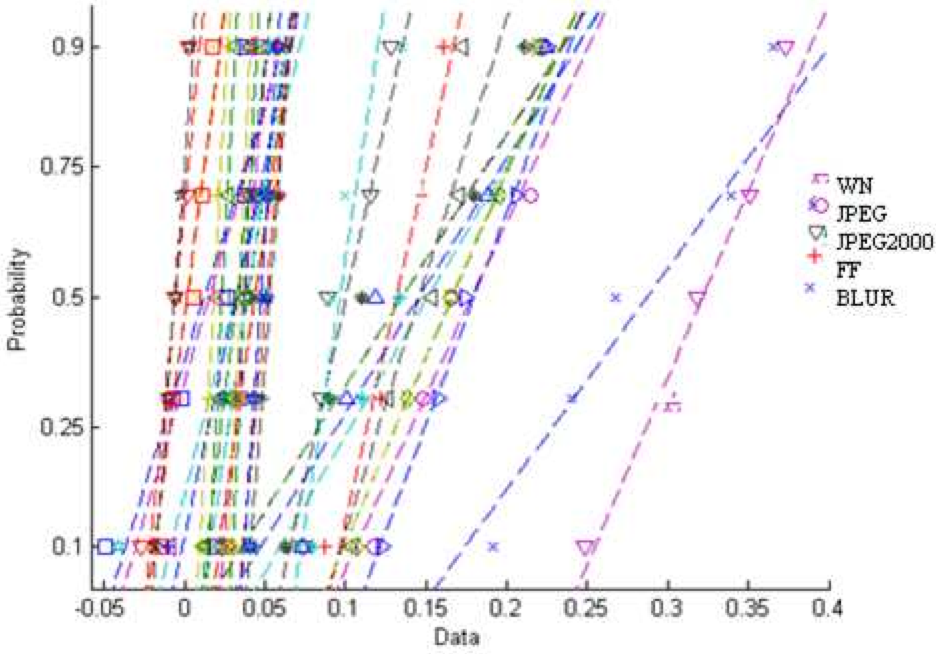

Fig 3.9. Probability for normal distribution using NRDPF-IQA

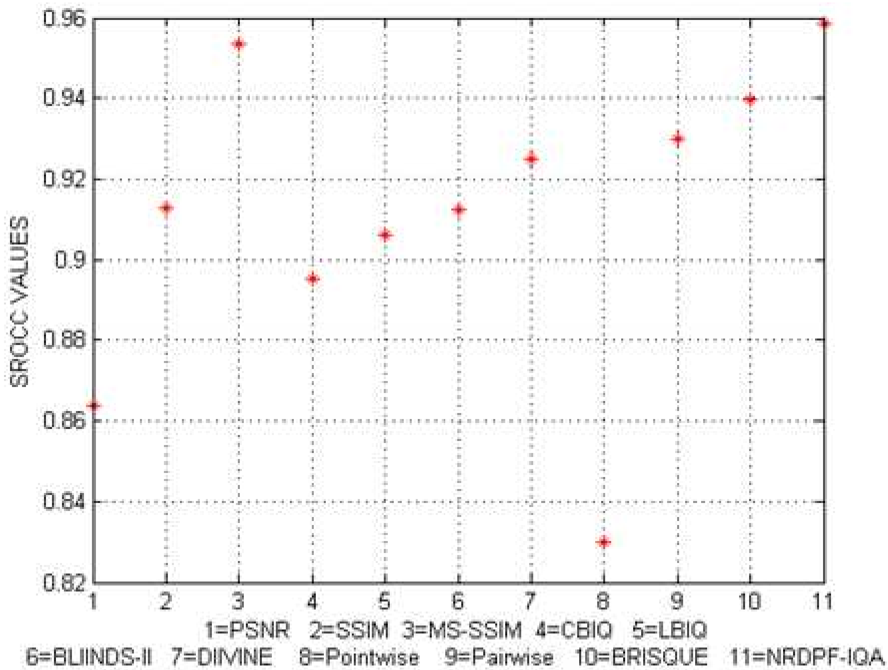

Fig.3.10. SROCC values verses NR-IQA methods

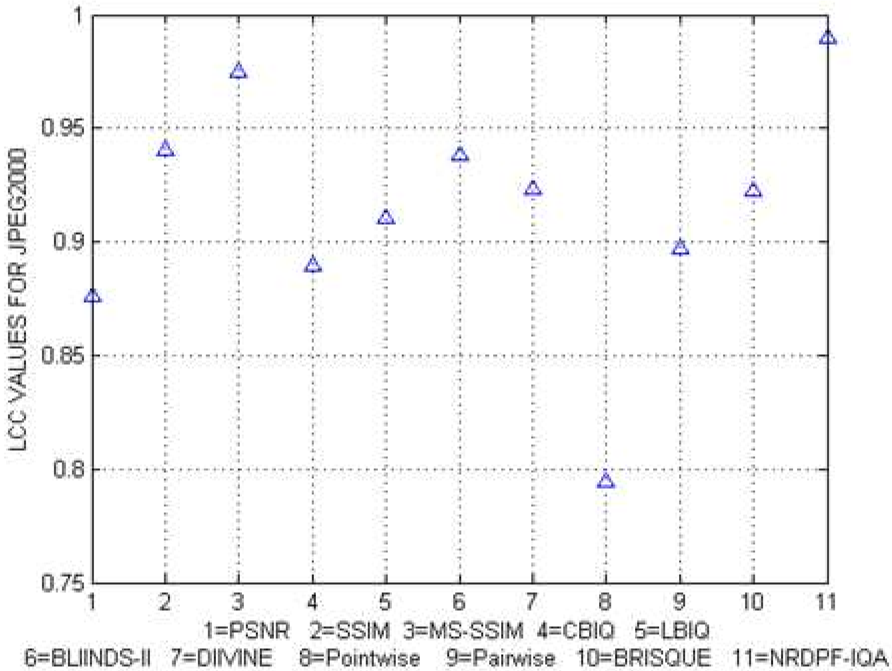

Fig.3.11. LCC values for JPEG2000 verses NR-IQA methods

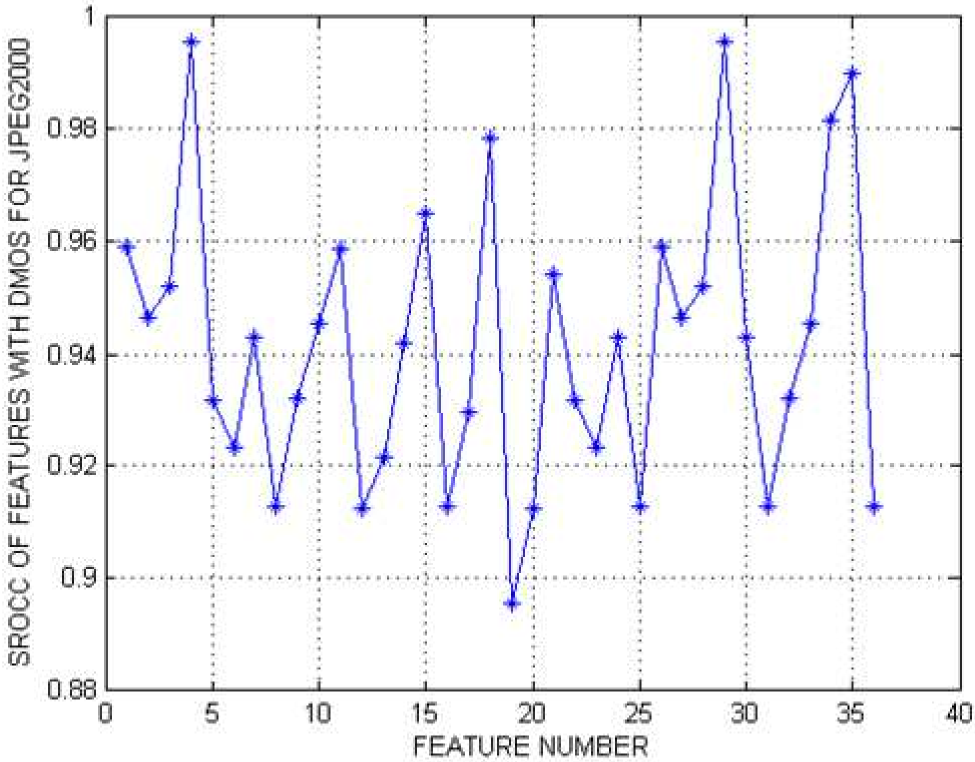

Fig. 3.12. SROCC of features with DMOS values verses feature number

Create Vignan University database for Image Quality Assessment:

36 input images were used to create a database whose results are being provided. The JPEG2000 used was Kakadu version 2.2. The testing procedure was as follows:

Thirty Six high-resolution 24-bits/pixel RGB color images were compressed using JPEG2000 with different compression ratios to yield a database of 180 images, 36 of which were the original (uncompressed) images. The compression ratios were considered as 1:0.3, 1:1, 1:2, 1:4, 1:8 and 1:16. The study was conducted in five sessions, with the original images included in all sessions. Study 1 contained images from 1.bmp to 36.bmp, study 2 contained images 37.bmp from to 72.bmp, Study 3 contained images from 73.bmp to 108.bmp, study 4 contained images from 109.bmp to 144.bmp, and study 5 contained images from 145.bmp to 180.bmp. The bit rates were chosen as 0.5bpp, 1bpp, 2bpp, 4bpp, 8bpp and 24bpp such that the resulting distribution of quality scores for the compressed images was roughly uniform over the entire range.

Each observer was shown the images randomly. Observers were asked to provide their perception of quality on a continuous linear scale that was divided into five equal regions marked with adjectives ”Bad”, ”Poor”, ”Fair”, ”Good” and ”Excellent”. The scale was then converted into 1-10 linearly. The testing was done in five sessions with about ten images in each session. No viewing distance restrictions were imposed, display device configurations were identical and ambient illumination levels were normal indoor illumination. Subjects were asked to comfortably view the images and make their judgements. A short training preceded the session. A bit rate of 0.00000 means a loss-less copy of the source file. The results are shown in fig.3.14 for vignan university database images. Few selected images and the corresponding scores are shown in table 3.10.

Subjective Score Files:

Each image in the database is followed by the scores given to it by the different subjects. A score of 0 means that the subject skipped the image.

Example:

1.

Bits per Pixel (bpp)= 0.5

CR=1:16

MSE=120.7

PSNR=27.3 db

Quality= 8.1629

2.

Bits per Pixel (bpp)= 1

CR=1:8

MSE=42.4

PSNR=31.9 db

Quality= 8.4268

3.

Bits per Pixel (bpp)= 2

CR=1:4

MSE=8.4

PSNR=38.9 db

Quality= 8.8912

4.

Bits per Pixel (bpp)= 4

CR=1:2

MSE=0.6

PSNR=50.2 db

Quality= 9.0126

5.

Bits per Pixel (bpp)= 8

CR=1:1

MSE=0.6

PSNR=50.2 db

Quality= 9.1272

6.

Bits per Pixel (bpp)= 24

CR=1:0.3

MSE=0.6

PSNR=50.2 db

Quality= 9.4168

Table 3.9: Median Spearman Rank Ordered Correlation Coefficient (SROCC) across 1000 train-test combinations on the LIVE-IQA database for different window sizes using NRDPF-IQA

K,L	Type of Distortion					
	JPEG2000	JPEG	WN	Blur	FF	ALL
4	0.9820	0.9803	0.9798	0.9605	0.9401	0.9489
5	0.9663	0.9715	0.9762	0.9597	0.9315	0.9461
6	0.9641	0.9642	0.9686	0.9497	0.9248	0.9419
7	0.9548	0.9618	0.9618	0.9427	0.9231	0.9345
8	0.9531	0.9512	0.9514	0.9329	0.9126	0.9258
9	0.9418	0.9465	0.9501	0.9301	0.9103	0.9186

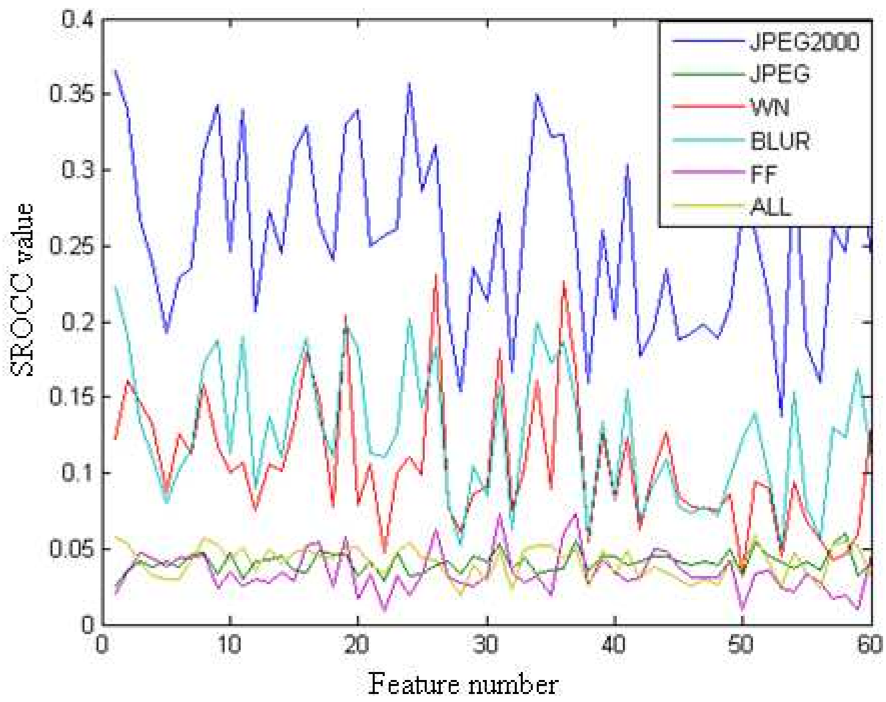

Fig.3.13. Image quality index performance for LIVE database

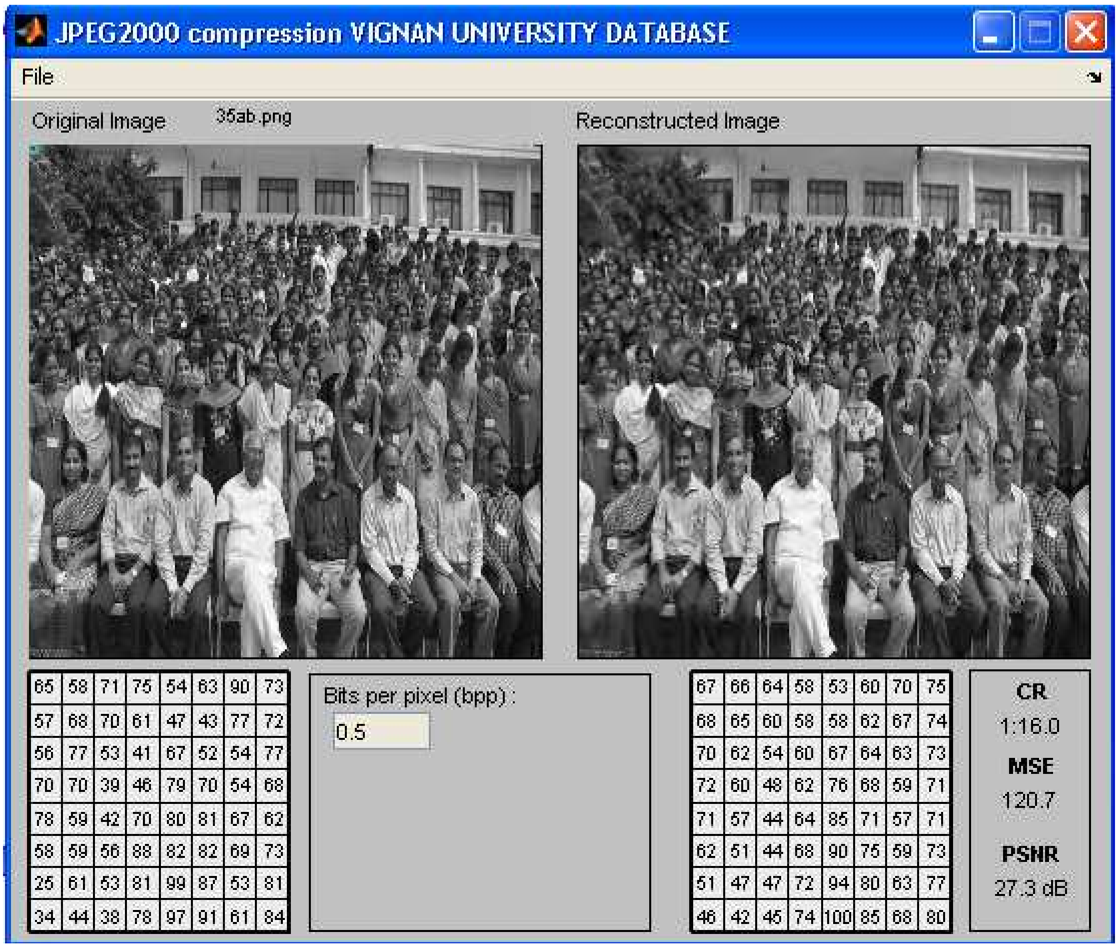

Fig. 3.14. Vignan University database for JPEG2000 compression images

Table 3.10: Quality scores for the selected images in Vignan University database

Database Image	Bits per Pixel (bpp)	CR	MSE	PSNR	Quality Score
35.bmp	0.5	1:16	120.7	27.3	8.1629
	1	1:8	42.4	31.9	8.4268
	2	1:4	8.4	38.9	8.8912
	4	1:2	0.6	50.2	9.0126
	8	1:1	0.6	50.2	9.1272
	24	1:0.3	0.6	50.2	9.4168
3.bmp	0.5	1:16	107.6	19.8	6.8412
	1	1:8	39.8	24.6	7.2145
	2	1:4	9.4	37.6	7.4861
	4	1:2	0.9	47.3	8.8198
	8	1:1	0.8	49.1	8.9002
	24	1:0.3	0.8	49.1	9.1648

Results of Vignan University database Using NRDPF-IQA Method

First, the database is established by JPEG2000 images and subjective experiments were conducted on the database. There are 36 test images in the database. 10 of them are original images. The rest are JPEG-compressed. 21 subjects were shown the database; most of them were the friends and adults with the age group of 19 to 53 years. The subjects were asked to assign each image a quality score between 1 and 10 (10 represents the best quality and 1 the worst). The 21 scores of each image were averaged to a final Mean Opinion Score (DMOS) of the image. After applying NRDPF-IQA method, the following are the quality index of images from 1 to 36. The individual scores of the vignan university database images are given in table 3.11.

Table 3.11: Individual quality scores for Vignan University database (for 36 images)

S.NO.	Image No.	Quality Index	S.NO.	Image No.	Quality Index
1	quality_img1	9.4683	19	quality_img19	2.8439
2	quality_img2	8.1629	20	quality_img20	2.9481
3	quality_img3	4.9668	21	quality_img21	2.4111
4	quality_img4	9.0987	22	quality_img22	2.5066
5	quality_img5	6.9973	23	quality_img23	2.8223
6	quality_img6	5.4157	24	quality_img24	3.0187
7	quality_img7	4.4739	25	quality_img25	2.5831
8	quality_img8	5.7546	26	quality_img26	2.4615
9	quality_img9	2.8535	27	quality_img27	2.4827
10	quality_img10	2.8384	28	quality_img28	2.1214
11	quality_img1 1	2.6380	29	quality_img29	2.0407
12	quality_img1 2	8.5648	30	quality_img30	2.3178
13	quality_img13	3.8174	31	quality_img31	3.5052
14	quality_img14	6.8286	32	quality_img32	3.2924
15	quality_img15	6.0599	33	quality_img33	2.7162
16	quality_img16	4.9783	34	quality_img34	2.9171
17	quality_img17	4.6705	35	quality_img35	2.5183
18	quality_img18	4.4739	36	quality_img36	3.6088

3.4. Summary

The suggested No reference Distortion Patch Features image quality assessment criteria, which perform better results in all available databases. NRDPF-IQA algorithm operates in the spatial domain. The results are confirmed with the individual understanding like Spearman and Pearson. The evaluation of the NRDPF-IQA design in terms of correlation with individual understanding and NRDPF-IQA is mathematically better than BRISQUE and other FR models. The results are confirmed by JPEG2000 images using LIVE database. Finally, new approach achieved the objects like execution of the No Reference Distortion Patch Features image quality assessment criteria depending on HVS [A-6], the criteria for No Reference Picture quality Assessment for JPEG2000 images depending on Human Visual System is examined [A-4], the performance of No Reference image quality depending on Human Perception is examined [A-3] and the informal complexity analysis of image quality depending on HVS is examined [A-5].

Chapter-4

QUALITY ASSESSMENT OF H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM

4. QUALITY ASSESSMENT OF H.264 VIDEOS BASED ON HUMAN VISUAL SYSTEM

4.1. Introduction

Bundle reduction will make severe mistakes due to the corruption of related video data. For most video sources, because the predictive programming components widely-used to, the transmitting errors in one framework will not only cause understanding failing of itself at the recipient side, but also distribute to its following supports along the activity forecast direction, which will bring a important destruction of end-to-end video quality. To quantify the effects of packet reduction on movie quality, a no-reference subjective quality assessment model is presented in this chapter. Considering the fact that the deterioration of movie quality significantly relies on video clips material, the temporary complexity is approximated to reflect the varying characteristic of movie material, using the macroblocks with different movement activities in each structure based on Human Visual System (HVS). The quality framework suffering from the recommendations framework decrease, by mistake reproduction, or by both of them is analyzed, respectively. Utilizing a two-level temporary pooling scheme, video clip quality is finally obtained. Extensive experimental results show that video clip quality approximated by the proposed method matches well with the available subjective quality.

The set of functions extracted is very similar to the one used for NR measurement in (Barkowsky et al., 2009). The functions are: blockiness, bluriness, activity and of a routine. The first three functions are dimensions for what occurs in every individual frame of video clip. Predictability describes what occurs between the individual supports of video clip, and is based on the assumption, that visible quality is perceived differently, if changes between nearby supports are smooth or if abrupt changes appear.

A no-reference video quality measurement for H.264 movie is introduced. The proposed method is No-Reference Distortion Patch Features Video Quality Assessment (NRDPF-VQA). This measurement analyzes a set of simple functions such as blocking or blurring, and combines those functions into one parameter comprising visible quality. While few base feature measurements are used, additional factors are acquired by analyzing changes for these measurements over time and using additional short-term combining methods based on HVS. To take into account the different features of different video sequence, the acquired quality is set using a low quality edition of the received video. The measurement is verified using information from accurate very subjective assessments, and additional care was taken to separate information used for calibration and verification. The proposed no-reference quality assessment delivers a prediction accuracy of 0.9312 when compared to very subjective assessments, and significantly outperforms PSNR as a quality predictor.

Confirmation of the suggested measurement was done using seven different original HD movie series secured using the AVC/H.264. Significantly different encoder configurations were applied to avoid training the models to one special encoder setting and also to account for a large quality variety, leading to bit rates from 0.5 Megabyte per second up to 50 Megabyte per second comprising a quality variety from “not acceptable” to “perfect” (0.21 to 0.94 on a 0 to 1 scale) and a total of 44 data points. All movie series have a spatial quality of 1920 × 1080 pixel and a temporary quality of 25 or 50 frames per second (fps). The very subjective assessments were performed using LIVE video database. The 95% assurance durations of the very subjective ballots are below 0.08 on a 0 to 1 variety for all single test cases, the mean 95% assurance period is 0.03.

4.2. No Reference Distortion Patch Features Video Quality Analysis

The strategy for the NRDPF- VQA (No Reference Distortion Patch Features Video Quality Assessment) can be described as follows. Given a (possibly distorted) video is having low bit amount, first estimate development and understanding of the supports chosen by video length. It also noticed that the stabilized luminance principles highly seem towards a device regular Gaussian attribute for video bases on Human Visual System.

4.2.1. Introduction to NRDPF-VQA Algorithm

The movement coherence tensor summarizes the prevalent movement guidelines over regional communities. The 2D movement coherence tensor at a given pixel is given in equation (4.2.1) by

$$S = \begin{bmatrix} f(M_x) & f(M_x.M_y) \\ f(M_x.M_y) & f(M_x) \end{bmatrix} \tag{4.2.1}$$

where

$$f(V) = \sum_{l,k} w[i,j]V(i-1, j-k)^2 \quad (4.2.2)$$

$M_x(i,j)$ and $M_y(i,j)$ are horizontal and vertical motion vectors at pixel (i, j) respectively, w is the screen of sizing m X m over which the nearby calculations of the tensor is conducted. The Eigen principles of the movement coherence tensor express details about the spatial positioning of the movement vectors within the screen of calculations.

This is successfully quantified by the coherence measure as given in equation (4.2.3)

$$C = \left(\frac{\lambda_1-\lambda_2}{\lambda_1+\lambda_2}\right)^2 \quad (4.2.3)$$

where λ_1 and λ_2 are the eigen principles of the movement coherence tensor. The 1-D general Gaussian solidity is an excellent fit to these coefficient histograms.

$$f(x|\alpha,\beta,\gamma) = \alpha e^{-(\beta|x-\mu|)^{\gamma}} \quad (4.2.4)$$

where μ is mean, γ is the form parameter, and α and β are decreasing and range factors given in equations (4.2.5) and equation (4.2.6) by

$$\alpha = \frac{\beta\gamma}{2\Gamma(1/\gamma)} \quad (4.2.5)$$

$$\beta = \frac{1}{\alpha}\sqrt{\frac{\Gamma(3/\gamma)}{\Gamma(1/\gamma)}} \quad (4.2.6)$$

where σ is the standard deviation, and Γ denotes the ordinary gamma function

$$\Gamma(z) = \int_0^{\infty} t^{z-1}\ e^{-t}dt \quad z>0 \quad (4.2.7)$$

The NRDPF-VQA algorithm is designed for this video quality evaluation purpose and similar features of the picture quality evaluation are implemented to implement the VQA model based on Human Visual System.

4.2.2. Implementation of NRDPF-VQA Algorithm

The strategy for the NR VQA has designed as follows. Given a (possibly distorted) video, first consider the frame size of the video and estimate regionally stabilized luminance via regional mean subtraction and divisive normalization (C.Li et al., 2010, C.Chen et al., 2013,). The each frame is considered for the calculation of quality. The following are the equations to used to a given strength movie.

$$H: \nabla_x I(i,j) = I(i,j+1) - I(i,j) \quad (4.2.8)$$

$$V: \nabla_y I(i,j) = I(i+1,j) - I(i,j) \quad (4.2.9)$$

$$MD: \nabla_{xy} I(i,j) = I(i+1,j+1) - I(i,j) \quad (4.2.10)$$

$$SD: \nabla_{yx} I(i,j) = I(i+1, j-1) - I(i,j) \tag{4.2.11}$$

$$HV: \nabla_x \nabla_y I(i,j) = I(i-1,j) + I(i+1,j) - I(i,j-1) - I(i,j+1) \tag{4.2.12}$$

$$CD_1: \nabla_{cx} \nabla_{cy} I(i,j)_1 = I(i,j) + I(i+1,j+1) - I(i,j+1) - I(i+1,j) \tag{4.2.13}$$

$$CD_2: \nabla_{cx} \nabla_{cy} I(i,j)_2 = I(i-1,j-1) + I(i+1,j+1) - I(i-1,j+1) - I(i+1,j-1) \tag{4.2.14}$$

$$J(i,j) = \log\,[I(i,j) + K] \tag{4.2.15}$$

$$D_1: \nabla_x J(i,j) = J(i,j+1) - J(i,j) \tag{4.2.16}$$

$$D_2: \nabla_y J(i,j) = J(i+1,j) - J(i,j) \tag{4.2.17}$$

$$D_3: \nabla_{xy} J(i,j) = J(i+1,j+1) - J(i,j) \tag{4.2.18}$$

$$D_4: \nabla_{yx} J(i,j) = J(i+1,j-1) - J(i,j) \tag{4.2.19}$$

$$D_5: \nabla_x \nabla_y = J(i-1,j) + J(i+1,j) - J(i,j-1) - J(i,j+1) \tag{4.2.20}$$

$$D_6: \nabla_{cx} \nabla_{cy} J(i,j)_1 = J(i,j) + J(i+1,j+1) - J(i,j+1) - J(i+1,j) \tag{4.2.21}$$

$$D_7: \nabla_{cx} \nabla_{cy} J(i,j)_2 = J(i-1,j-1) + J(i+1,j+1) - J(i-1,j+1) - J(i+1,j-1) \tag{4.2.22}$$

The equations from (4.2.8) to (4.2.22) signify the functions of the distortions areas. It also noticed that the stabilized luminance principles highly seem towards a device regular Gaussian attribute for video clip (low bit-rate) (G.Zhai et al., 2008).

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \tag{4.2.23}$$

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}\ I_{k,l} I(i,j) \tag{4.2.24}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}\,(I_{k,l} I(i,j) - \mu(i,j))^2} \tag{4.2.25}$$

$$f(x; \alpha, \sigma^2) = \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)} \exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{4.2.26}$$

$$\beta = \alpha \sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \tag{4.2.27}$$

$$\Gamma(a) = \int_0^{\infty} t^{a-1}\ e^{-t} dt \quad a>0 \tag{4.2.28}$$

$$f(x, \rho) = \frac{\exp\left(\frac{|x|\rho}{1-\rho^2}\right) K_0\left(\frac{|x|}{1-\rho^2}\right)}{\Pi\sqrt{(1-\rho^2)}} \quad x<0 \tag{4.2.29}$$

$$f(x; v, \sigma_l^2, \sigma_r^2) = \begin{cases} \frac{v}{\beta_l + \beta_r \Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{-x}{\beta_l}\right)^{v}\right) \\ \frac{v}{\beta_l + \beta_r \Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{x}{\beta_r}\right)^{v}\right) \end{cases} \quad x \geq 0 \tag{4.2.30}$$

$$\beta_l = \sigma_l \sqrt{\frac{\Gamma(1/v)}{\Gamma(3/v)}} \tag{4.2.31}$$

$$\beta_r = \sigma_r \sqrt{\frac{\Gamma(1/v)}{\Gamma(3/v)}} \quad (4.2.32)$$

$$\eta = (\beta_r - \beta_l) \frac{\Gamma(2/v)}{\Gamma(1/v)} \quad (4.2.33)$$

$$b_0 = \frac{\sum_{i=1}^{N} X_{(i)}}{N} \quad (4.2.34)$$

$$b_r = \frac{\sum_{i=r+1}^{N} \frac{(i-1)(i-2)\dots.(i-r)}{(n-1)(n-2)\dots.(n-r)} X_{(i)}}{N} \quad (4.2.35)$$

$$l_1 = b_0 \quad (4.2.36)$$

$$l_2 = 2b_1 - b_0 \quad (4.2.37)$$

$$l_3 = 6b_2 - 6b_1 + b_0 \quad (4.2.38)$$

$$l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \quad (4.2.39)$$

Thus for each combined item, 36 factors (6 parameters/orientation X 6 orientations) are calculated, producing the next set of functions.

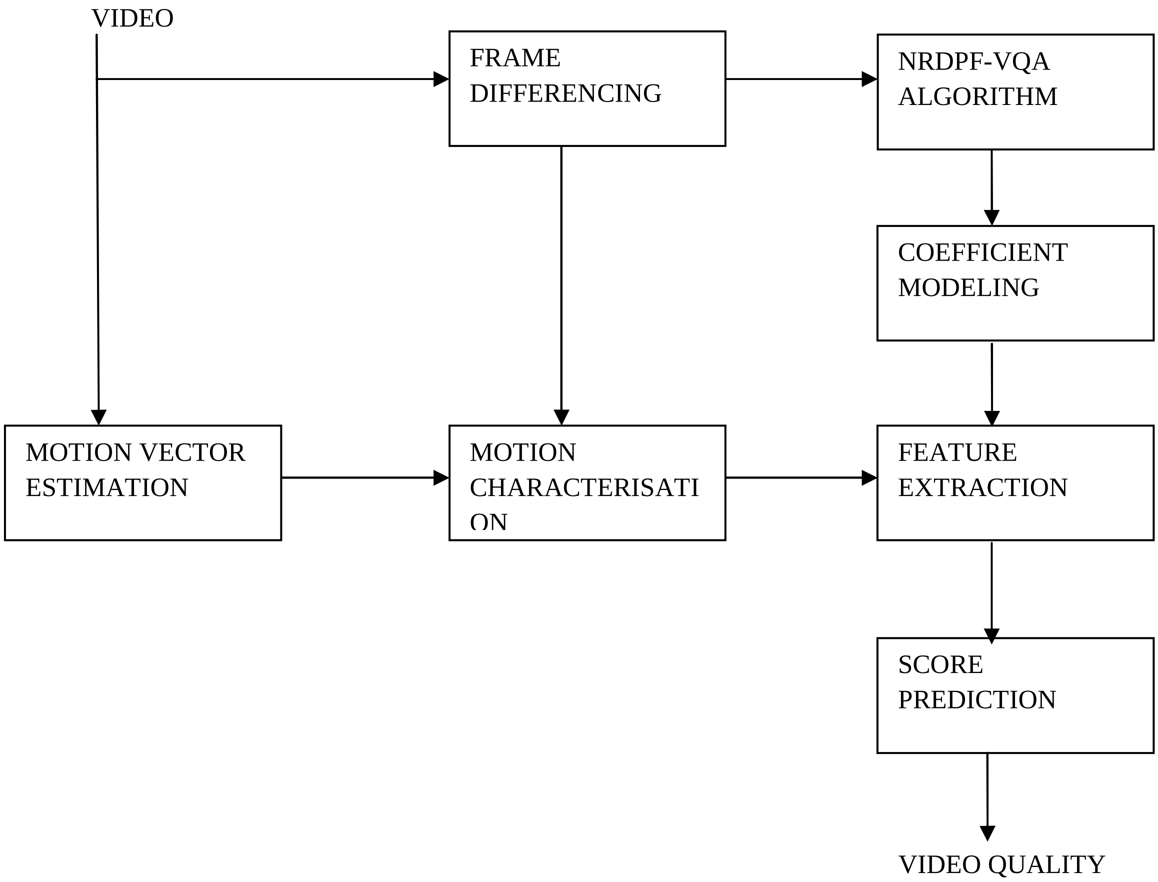

Fig. 4.1. Video Quality Assessment using NRDPF-VQA algorithm.

The above block diagram shows that the procedure for usage of the NRDPF-VQA criteria in picture quality analysis shown in fig. 4.1. Finally, Video quality score is measured using this criterion.

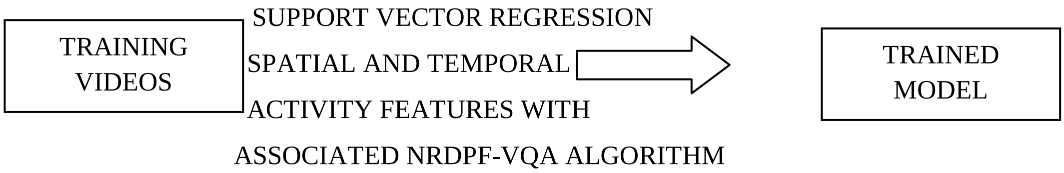

Fig. 4.2. Learning frame work

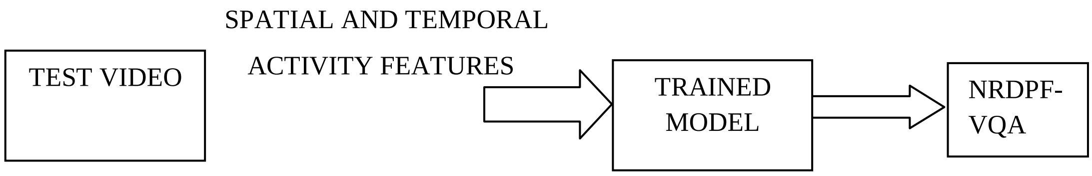

Fig. 4.3. NRDPF-VQA model frame work

A video's temporary material using a 2D framework tensor design used to a video's calculated movement vectors are defined. An easy movement vector evaluation a criterion is used on n X n prevents to figure out the corresponding spatial place of prevents in one framework in the successive framework in time. The movement evaluation is conducted via a easy three-step look for criteria. The movement coherence tensor summarizes the prevalent movement guidelines over regional communities. The learning framework and model framework are shown in fig.4.2 and fig.4.3 respectively. The 2D movement coherence tensor at a given pixel is considered. Vertically and horizontally movement vectors at pixel (i; j) respectively, and w is a screen of sizing m X m over which the nearby calculations of the tensor is conducted.

The Eigen principles of the movement coherence tensor express information about the spatial positioning of the movement vectors within the screen of calculations. The comparative difference between 2 Eigen principles is an indication of the level of anisotropy of the local movement (in the window), or how highly the movement is one-sided towards a particular route. This is successfully quantified by the coherence evaluate where λ_1 and λ_2 are the Eigen principles of the movement coherence tensor. The design records for the scale of movement. This is calculated simply as the method of the movement vectors between every two successive supports. The mean of the method is calculated across video clips series and used as a function during the ranking forecast stage. A good NVS (natural video statistics) design should catch regular and foreseeable mathematical actions of organic video clips based on HVS. Such designs could be used to evaluate the level of disturbances in movie alerts since disturbances may obviously change these researches (T.Liu et al., 2009).

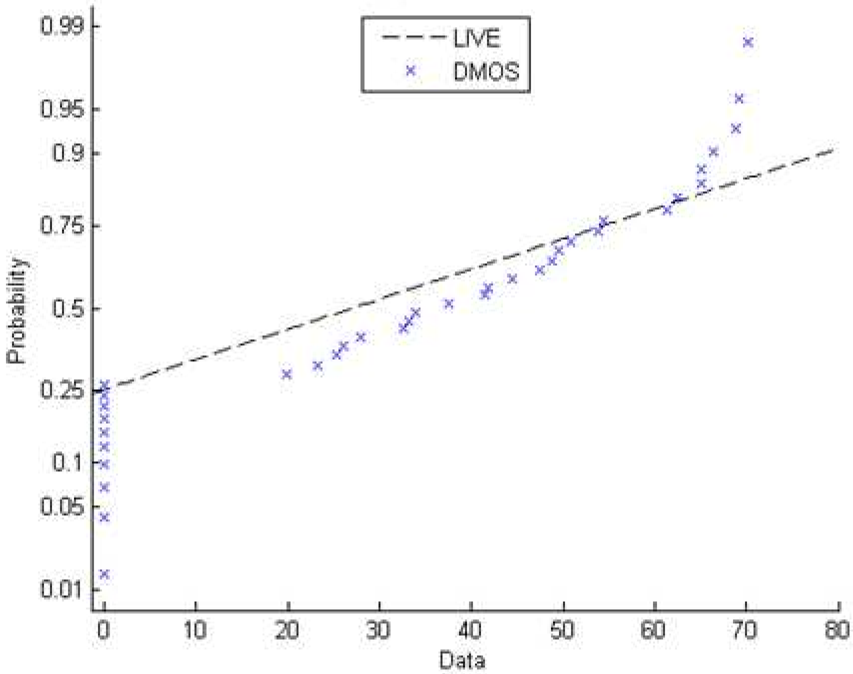

Fig.4.4. Probability for DMOS using NRDPF-VQA model (only H.264 format)

In the following, it recommend an NRDPF-VQA design of structure variations that is indicated and determine a variety of perceptually appropriate functions that are produced from the design factors. It starts by explaining NRDPF-VQA design coefficients of distortion patch features variations. It talks about the movement research procedure and how it is used to bodyweight the factors of the spatio-temporal design. The probability plot for DMOS using NRDPF-VQA model for H.264 is shown in fig. 4.4.

Consider video clips series containing M supports, each structure listed (i + 1) is deducted from structure leading to difference-frames. Each distinction structure is then portioned into n X n patches or prevents. The coefficients from prevent in each distinction structure are made as following a general Gaussian possibility submission. Given a movie structure, there are n X n prevents per structure, each containing nXn regularity coefficients. Thus each of the n X n regularity coefficients in prevent happens n X n periods per difference-frame. The histogram of each regularity coefficient from all n X n areas with a parametric solidity operate is fitted in each distinction structure. It may be noticed that the coefficients are symmetrically allocated around zero and that the coefficient withdrawals at different wavelengths display different stages of peakedness and distribute about their assistance. This encourages the use of a group of withdrawals that involves a variety of end actions.

This depiction is generally different between organic video clips and altered ones. The NRDPF-VQA method is designed to catch this mathematical difference and evaluate it for perceptual movie quality ranking forecast. DMOS response for H.264 format using LIVE database is shown in fig.4.5.

Each n X n matrix of shape-parameters per distinction structure is portioned into three sub-bands as portrayed, where the remaining group matches to shape-parameters modeling low-frequency coefficients, the center partition matches to mid-band wavelengths, and the reduced right partition matches to high-frequency coefficients. Estimate a percentile regular of the form factors per band, the mean of the biggest 10% of the form factors per group is calculated. Thus for each structure distinction, the following mathematical functions are computed: 1) tenth-percentile low regularity group form parameter, 2) tenth-percentile mid-band form parameter, and 3) 10th percentile great regularity group form parameter.

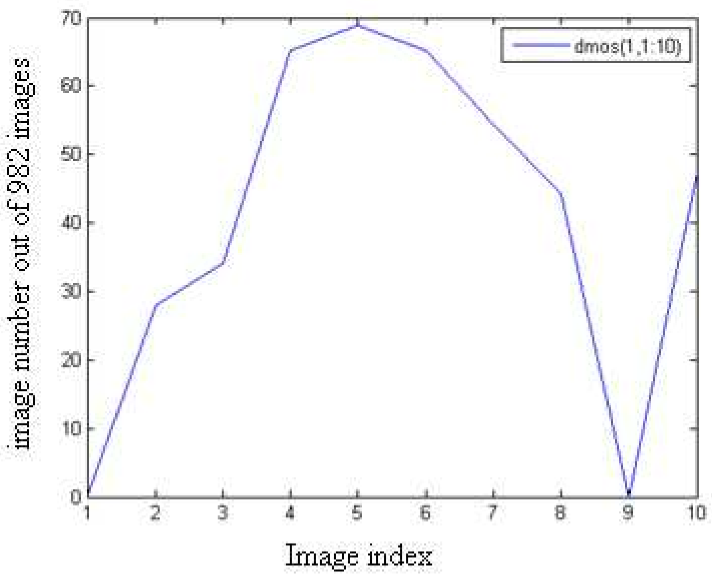

Fig. 4.5. DMOS response for H.264 video format

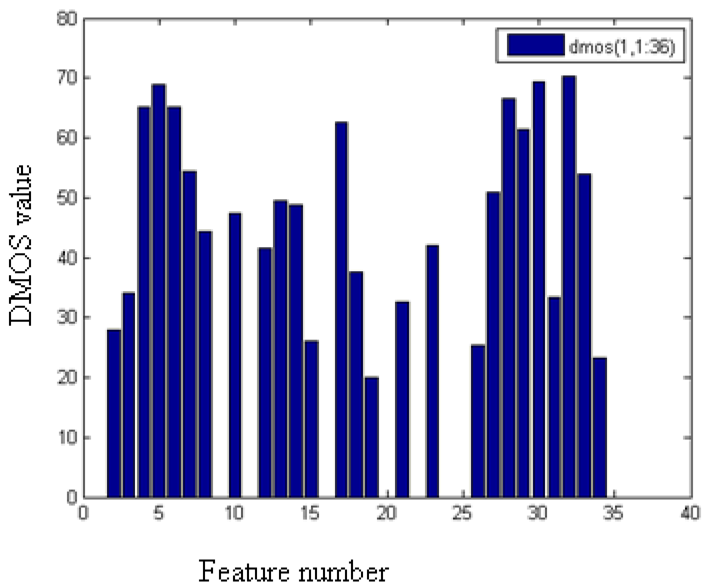

Fig. 4.6. DMOS response for 36 features for H.264 video format

To track temporary modifications in the common concentration of differenced movie frames, the distinct temporary mixture of the common strength per movie structure is also calculated. The DMOS response for 36 features bar chart for H.264 video format in LIVE database is shown in fig.4.6. This is a simple measure of sudden regional changes which may occur from various temporary disturbances that result in regional ‘flicker’.

4.3. Performance Analysis of No Reference Video Quality

Given a database of distorted videos and associated individual decision, the extracted features are used to practice a straight line kernel support vector regressor (SVR) to perform movie quality ranking forecast. The temporary scale of the process by producing temporary ratings in two ways: 1) by producing ratings on an instantaneous (frame) foundation, and 2) by developing quality ratings over 10 second durations. Since DMOS ratings on VQA databases are usually only reported for complete movie segments (10 seconds), the NRDPF-VQA method applied on a structure foundation against the distorted movie for individual ratings. In this way it is possible to practice the SVR to generate structure quality ratings. Subjective DMOS ratings were used to practice another SVR to predict quality ratings over 10 second movie durations. In both cases, a straight line kernel SVR based on the execution was used to perform quality ranking forecast. The results are tabulated in Table 4.1.

Table 4.1: Median SROCC correlations on every possible combination of train/test set splits (subjective DMOS vs NRDPF-VQA DMOS) for H.264 videos. 80% of content used for training

Type of Distortion	Method							
	PSNR	SSIM	VQM	STMAD	MOVIE	RRED	VIDEO-BLIINDS	NRDPF-VQA
MPEG-2	0.667	0.786	0.828	0.9484	0.928	0.809	0.882	0.9514
H.264	**0.714**	**0.762**	**0.828**	**0.9286**	**0.904**	**0.885**	**0.851**	**0.9312**
Wireless	0.680	0.714	0.714	0.7976	0.800	0.771	0.802	0.8124
IP	0.660	0.600	0.770	0.7143	0.788	0.771	0.826	0.8436
ALL	0.671	0.650	0.745	0.8250	0.807	0.826	0.821	0.8514

4.3.1. Introduction

A database of altered video clips and associated human decision, the extracted features are used to train a straight line kernel support vector regressor (SVR) to conduct movie quality score prediction. The temporary scale of the process by producing temporary ratings by producing temporary ratings on structure angles and by developing quality ratings over 10 second interval. Since DMOS ratings on VQA data source are usually only reported for complete movie segments of 10 seconds, it is tested in the SVR to generate structure quality ratings. Subjective DMOS ratings were used to predict quality ratings over 10 a few moments' movie intervals. The results are shown in fig.4.7 (a - g) for H.264 movie format with 10 frames.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Fig. 4.7. Video frames (images) from (a) to (g) are consider for H.264 Video with low bit rate.

4.3.2. LIVE VQA database

LIVE VQA database is used to test the performance of NRDPF-VQA criteria, which made up of 142 movie clips in different categories like MPEG-2, H.264, wireless, IP. Out of which, it tested using H.264/AVC format movie clips. Each of the distortions movie clips has an associated difference mean opinion score (DMOS) which symbolizes the very subjective quality of video clip. Since NRDPF-VQA strategy, to make sure that the revealed results do not rely on features produced from known content, which can synthetically enhance efficiency. Further, this unique analyze process LIVE VQA database, in order to remove efficiency prejudice. The experimental setup is shown in fig.4.8.

To create a set of altered movie clips for the research, eight uncompressed raw resource movie clips of quality that are freely available for researchers from LIVE database. This material has previously been used as resource material in the LIVE movie quality evaluation Data resource, which is currently a popular database used to test the performance of VQA methods. The movie clips used in the research are all naturalistic, meaning that they were taken with common digicam under common conditions with as little disturbances as possible. These organic movie clips are also free of synthetic material, such as graphics, animated graphics, text overlays or computer customized data. The features that extract from these movie clips obtain from perceptually relevant organic scene figure designs. These kinds of designs have been used to understand and explain certain properties of visible perception to model disturbances processes in images and videos for technological innovation quality evaluation methods.

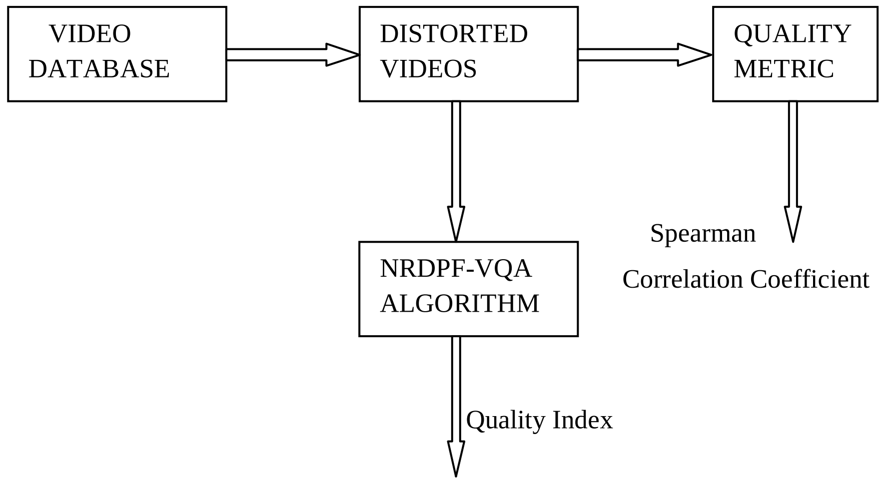

Fig.4.8: Testing process for all video databases

Video clips were shot using a professional movie digicam and are recorded in aYUV420P format, without sound. While the relationship between movie and sound has been analyzed, and certain results may be made from such perform, do not attempt to research the connections between the two here, choosing instead, to research the visible losslessness of movie clips only, to isolate the effects of pressure on visible experience. Given the development of similar designs for sound, along with the designs of audio-visual connections, audio-video lossless pressure measures are logical progresses of this perform.

The video clips were down tested from 1280 × 720 to a quality of 768×432, using MATLAB's imresize operate which uses bicubic interpolation. This was done due to source restrictions based on the video card and the processer utilization. To make the altered video clips, the referrals encoder for H.264/AVC used. Each video clip was compacted using eight different bit prices, tested consistently on a log scale: 0.5, 0.6198, 0.7684, 0.9526, 1.1810, 1.4640, 1.18150 and 2.2500 Megabyte per second. The bit amount variety choice for this research was done based on a small set of (different) video clips compacted over a bigger set of bit rates. The guideline information of the H.264 encoder was used for pressure with an I-frame period of 16 and with the rate-distortion marketing choice allowed. Three piece categories were used per structure with 36 macro prevents per piece and an allocated versatile macro prevent purchasing method. While different these factors and learning their results on visible quality stay of interest, in the existing work, learning the VL limit as operate of the bit-rate is limited.

4.3.3. Comparison with existing Algorithms

Once the (binary) choices were gathered from each user, a mathematical research to calculate the VL limit for each of the video clips is conducted. VRDPF-VQA test for equivalent medians to assess whether the submission of ratings allocated to the compacted movie had an average value similar to that of the ratings allocated to the video. However, to account for human prejudice, the outcomes with subjective outcomes are compared. In situation the withdrawals match (in the mathematical sense of their medians matching) then the compacted movie is assumed VL, else the topic is considered able to understand the disturbances. The results are shown in fig.4.9.

The most of the videos were able to properly assess the altered movie from the distorted–reference couple whereas verdict was unique. The zero speculation was that the two withdrawals (compressed–video ratings and No–Reference video scores) come from withdrawals with equivalent medians. The outcomes of such research carried out at the 95% stage of assurance are given for each of the video clips. A ‘0’ in the table indicates that the zero speculation cannot be refused at the 95% stage of assurance, which indicates that the compacted movie is perceptually identical to the referrals movie. While this might be due to small number of topics who took part in the research, it is also possible that the bit rates used did not entirely period the range from VL to completely obvious for these materials. In all video clips, the biggest bit-rate corresponding to a ‘1’ is used as the VL bit-rate. The results are shown in fig.4.10. However, video is already at the VL stage at a bit-rate of 0.5 Megabyte per second, and hence 0.5 Megabyte per second is considered as the VL limit for this video.

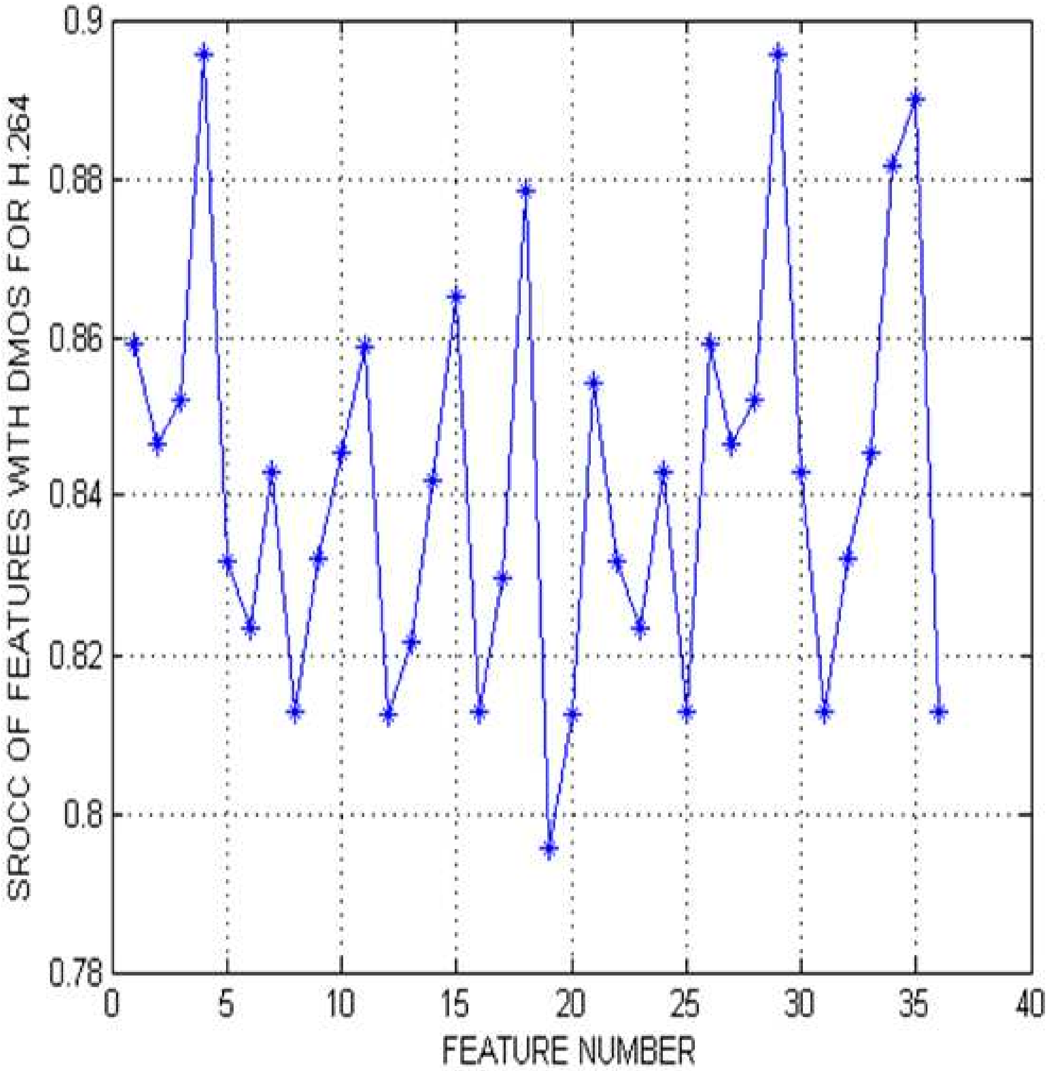

Fig.4.9. SROCC of features with DMOS for H.264 verses feature number

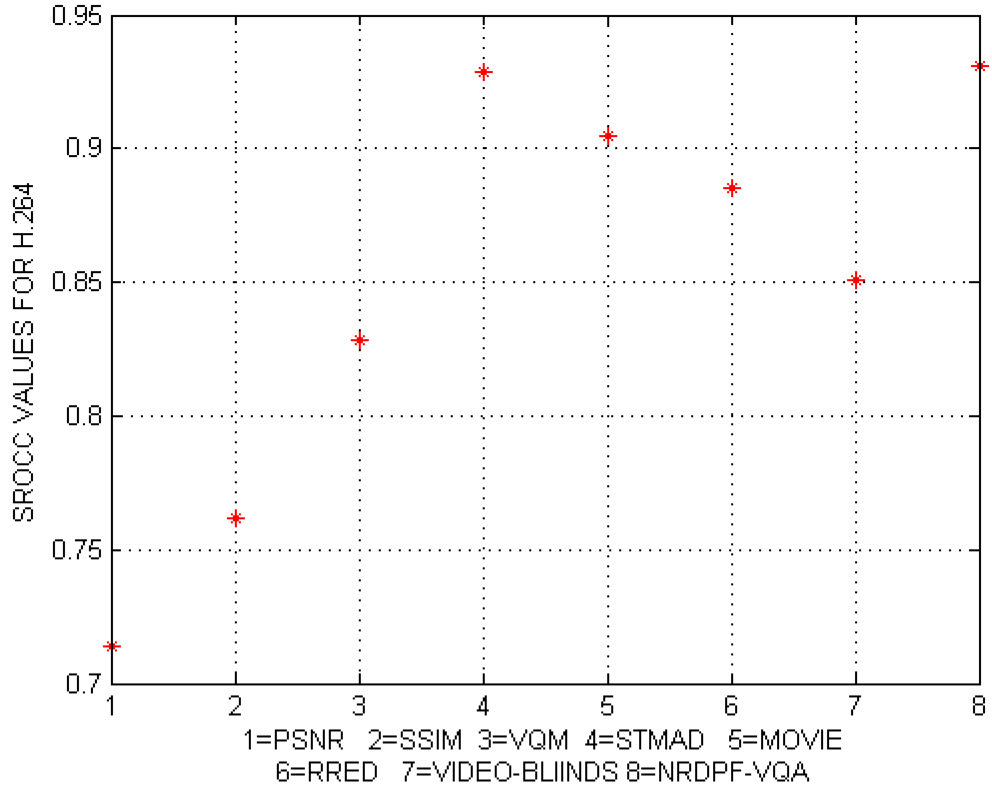

Fig.4.10. Comparing all existing NR-VQA methods with NRDPF-VQA method

4.3.4. Results and Discussions

While using a probabilistic structure for disturbances category where the prospect of movie being altered with a particular disturbances, but just as an evidence of how excellent functions used in the structure act as disturbances identifiers and also which disturbances are misclassified with which ones. The each access in the matrix is the mean across video database. Database that H.264/AVC structure is examined with other types. Also, MPEG-2 and IP are also examined. White-noise and Cloud are relatively more effective in recognition and usually with other disturbances. The results are shown in fig.4.11.

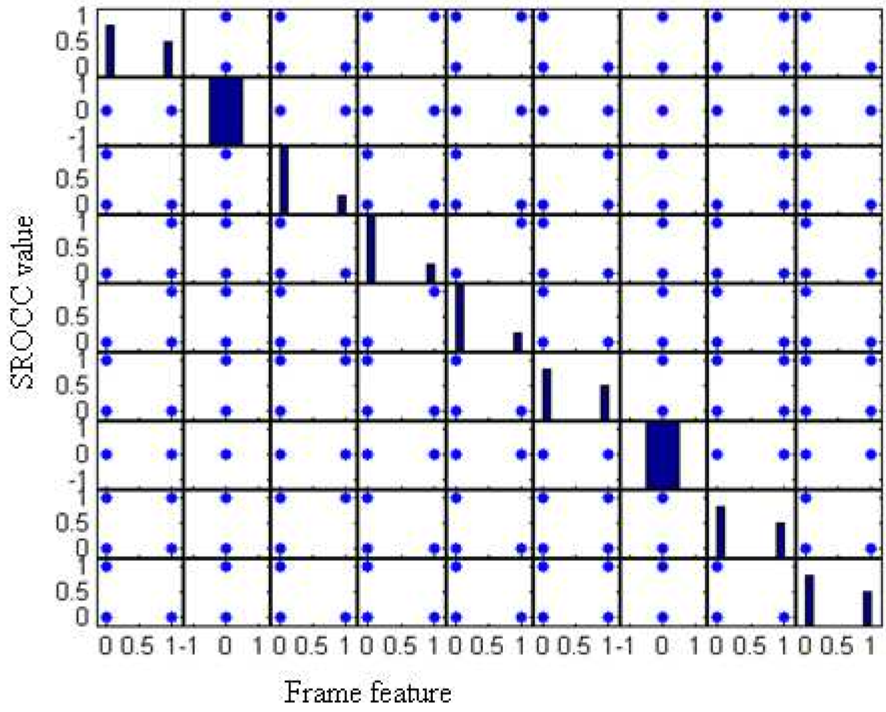

Fig.4.11. Frame features for H.264 video format

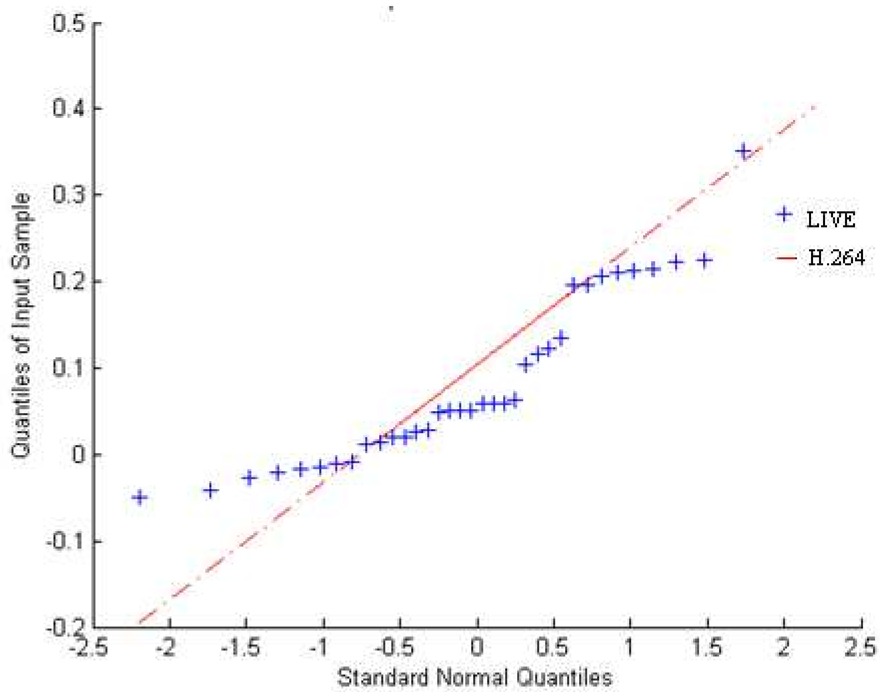

Fig. 4.12. 10 frames sample for H.264 video format

LIVE VQA database is used to analyze the efficiency of NRDPF-VQA criteria, which made up of 142 video clips in different groups like MPEG-2, H.264, Wi-Fi, IP. Each of the distortions video clips has an associated distinction mean viewpoint ranking (DMOS) which symbolizes the very subjective quality of the video clip. The results are shown in fig.4.12.

Since NRDPF-VQA strategy, to make sure that the revealed results do not rely on features produced from known content, which can synthetically enhance efficiency. The results are shown in fig.4.13. Further, this unique analyze process LIVE VQA data source, in order to remove efficiency prejudice. Thompson Multiplier PSDE values for the videos from (a) to (h) and corresponding SROCC values with respect to bit rate is shown in fig.4.14. The Results of 2-Alternative Forced Choice (AFC) task is shown in table 4.2.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

Fig. 4.13. Video quality index performance for selected database for testing from (a) to (h)

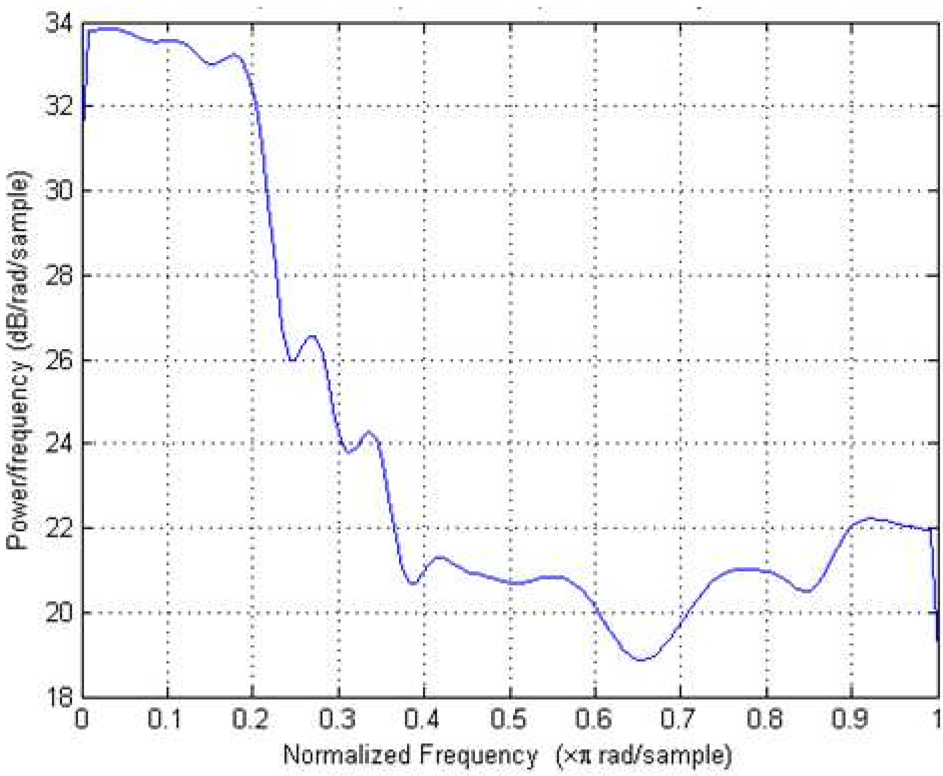

Fig.4.14. Thompson Multiplier PSDE values for the videos from (a) to (h) and corresponding SROCC values with respect to bit rate

Table 4.2: 2-Alternative Forced Choice (AFC) task

Selected VIDEO	VIDEO (Mbps)							
	0.50	0.62	0.77	0.95	1.18	1.46	1.81	2.25
VIDEO a	1	1	1	1	1	0	1	0
VIDEO b	1	0	1	1	1	0	1	1
VIDEO c	1	1	0	1	0	1	0	1
VIDEO d	0	1	0	1	1	0	1	0
VIDEO e	1	0	1	1	1	1	1	1
VIDEO f	1	1	1	1	1	1	1	1
VIDEO g	1	1	1	1	0	1	1	1
VIDEO h	1	1	1	1	0	1	0	1

4.4. Low bit rate Video Quality Analysis Using NRDPF-VQA Algorithm

Having mathematically examined the VL limit, it could simply have mentioned the VL bit-rates, depending on an irrelevant category depending on movement or spatial action. However, a simple human category may be inadequate to address the general situation where a formerly hidden movie is to be examined to instantly draw out a VL limit. Hence, as an initial step, the video clips are evaluated by getting actions of (1) spatial action and (2) temporary action, which uses NRDPF-VQA to create an criteria that is capable of forecasting the VL limit for a formerly hidden movie. The video quality assessment for H.264 videos of Vignan University (VU) database results are shown in fig.4.15. Spatial action is evaluated of the quantity of difference in the field, while temporary action is evaluate of the quantity of movement. Both of these are related to perceptual covering up and hence, to distortions exposure.

Table 4.3: Ground truth and NRDPF-VQA for videos (a), (c), (d), (f) and (g) from LIVE VQA database (only selected).

Model	Selected Videos				
	a	c	d	f	g
Actual	0.9500	1.4600	1.1800	1.1800	0.5000
VL bit-rate	1.0923	1.2651	1.1981	1.0189	0.9365
NRDPF-VQA (Proposed)	**1.0021**	**1.3642**	**1.1842**	**1.1792**	**0.6245**

The steerable chart breaking down is an over finish wavelet convert that has been commonly used for explaining the research of natural pictures, for picture quality evaluation. The steerable chart breaking down allows for a multi-scale multi-orientation breaking down just like that which is hypothesized to happen in area of the main visible cortex.

Each structure of video clip is decomposed using the steerable chart breaking down over eight orientations. Formerly, it has confirmed that NRDPF-VQA is an excellent evaluate of spatial action in video. Group successfully pass narrow coefficients of a low action sub-band have bigger kurtosis value linked to most coefficients having near zero principles resulting in possibility submission to be peaky. Evaluate of action is simply the mean kurtosis value across sub groups.

Thus, the execution of the compressibility catalog for H.264 includes a SVM that regress actions of spatial and temporary action onto a bit-rate corresponding to the VL limit for that movie. The H.264 Visually Lossless Compressibility is the first criteria that forecasts VL limit bit rate for H.264 compressed movie clips.

(a) Q=5.7814 (b) Q=6.8426 (c) Q=7.9426

Fig.4.15. Quality scores for Vignan University database for H.264 videos

4.5. Summary

H.264 Innovative Movie format is conventional for video programming that defines a structure or structure for compacted video or a method of understanding this structure. It provides a set of resources or methods that can be used to provide effective, versatile and effective video compression for a variety of programs, from low-complexity, low bit rate mobile video applications to high-definition transmitted services.

NRDPF-VQA analyzes H.264 video format based on Human Visual System features and efficiency of proposed method performs good results compared with other NR-VQA methods. Finally, No Reference Distortion Patch Features Video Quality Assessment algorithm for H.264 videos based on Human Visual System is developed [A-7], the Low bit rate Video Quality Analysis Using NRDPF-VQA algorithm [A-1] is studied, and the visually lossless level Video Quality Assessment using NRDPF-VQA algorithm [A-2] is studied.

Chapter-5

CONCLUSIONS AND SCOPE FOR FUTURE WORK

5. CONCLUSIONS AND SCOPE FOR FUTURE WORK

5.1. Conclusions

The main contribution of this work is to implement a new approach for no reference image and video quality assessment based on human visual system especially for JPEG2000 and H.264 formats. A method of No Reference Distortion Patch Features Image and Video Quality Assessment (NRDPF-IQA/VQA) design technique is proposed for image/video quality assessment using distortion patch features and L-moments. A better connection with human decision of picture quality is achieved when distortions vary from natural scene statistics models. The algorithm quantifies the naturalness in the image due to presence of distortions. The designed frame work is in spatial domain, simpler and faster which makes it superior to other no reference algorithms.

However, NRDPF index has been shown to perform well across different distortions verifying its distortion agnostic nature. An exhaustive analysis of performance is done using LIVE and Vignan University databases for images and videos. The technique is effective and even performs better when only little bit of training data is available for learning the structure.

5.2. Contribution to the Knowledge base

In this work, an effective technique is developed to evaluate the image and video quality. The principal contributions are determined as follows.

1. A novel approach to implement the No Reference Distortion Patch Features Image Quality assessment algorithm based on Human visual System is designed.
2. An algorithm for No Reference Image Quality Assessment for JPEG2000 images based on Human Visual System is implemented and experimented using available databases.
3. The performance of No Reference Image Quality based on Human Perception is analyzed.
4. The informal complexity analysis of Image Quality based on HVS is studied.
5. The No Reference Distortion Patch Features Video Quality Assessment algorithm for H.264 videos based on Human Visual System is implemented and experimented using available databases.

6. The Low bit rate Video Quality Analysis Using NRDPF-VQA algorithm is achieved using the H.264 videos.
7. The visually lossless level Video Quality Assessment using NRDPF-VQA algorithm is achieved for low bit rate videos.

There are many challenges remaining to be resolved in the field of no reference image and video quality assessment methods. There is a wide scope for the development of improved reliable image/video quality metrics. For example, post processing effects and scaling the video in the temporal, spatial or SNR dimension in conjunction with display on wide range of devices, call for new video quality assessment methods. Furthermore, the notion of video quality is currently being broadened to the notion of Quality of Experience, which encompasses the complete context of the video consumption experience. The results show that the performance of the developed design is excellent in both image quality evaluation and video quality evaluation. The developed video quality evaluation technique is well suited to the real-time cellular video applications, such as the videophone and cellular IPTV.

The current design only concerns the frame of video material but does not consider the impact of the total video quality. Further performance should include the development of a more precise way to explain complete video. A thorough assessment of the NRDPF-IQA/VQA collection with regards to relationship with personal knowing is done and verified that NRDPF-IQA far better in statistics than FR PSNR and SSIM as well as incredibly competitive to all NR methods contrary to.

5.3. Scope for Future Work

The participation in this work can be utilized and prolonged in various ways. One can use this work as a methodical literary works evaluation to execute comparisons on a type of NR techniques using the same image or video analyze database to emphasize the state-of-the-art. Furthermore, this evaluation can be very useful for the beginner researchers to accomplish a small yet comprehensive overview of quality assessment. The contribution to be important for upcoming analysis and development in NR quality evaluation is anticipated. Moreover, a possible upcoming work is to study the contributions for audio-visual quality evaluation depending on NR paradigm that offers with FR techniques of audio-visual quality evaluation.

Upcoming works will concentrate on an expansion of the present database in order to consist of disturbances due to jitter and delay. Future direction of the work is to utilize the recent developments in color perception in the Human Visual System models. Also, further research on the impact of the ecological circumstances over the results of the subjective tests will be conducted, concentrating on the cellular situation, where the evaluation of video quality at spatial domain is more genuine.

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PUBLICATIONS BASED ON THE RESEARCH WORK

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