



## White Paper: Understanding MOS, JND, and PSNR

*Bill Reckwerdt, CTO  
Video Clarity, Inc.*

The term video quality remains poorly defined even in cases where it seems that it shouldn't be. It comes down to the word "quality". Quality depends on the "reference" and that "reference" may be of low appeal. How do you quantify quality when the "reference" has no appeal? We often think in terms of how far the quality is from "pristine", but that word causes even more grief, and let's not get started on "similarity" or "fidelity". Where do we start in defining video quality?

We must start at the beginning and define what we want to achieve. Are we trying to measure the perceived effect when we know that the video quality has been degraded? Perhaps, we want to know if the video quality is equal to what we already know is good?

It all starts with a simple concept; we must judge video quality in a "consistent" way; regardless, of the type of distortion.

## General Video Quality Defined

We are using video quality to define 3 components:

- Picture Quality – an index of eyes ability to understand the picture
- Audio Quality – an index of the ears ability to discern the audio
- Lip Sync – a measurement of the audio to video synchronization

We are also going to define 2 terms:

- Metric – an algorithm that quantifies differences
- Index – an algorithm that measures quality using the Human Visual or Audio System (HVS/HAS)

Ultimately, there is only 1 proven way to evaluate video quality and that is Subjective Testing. However, this is very expensive, time-consuming, and often impractical. The main subjective quality methods are Degradation Category Rating (DCR), Pair Comparison (PC) and Absolute Category Rating (ACR). The human subjects are shown 2 sequences (original and processed) and are asked to assess the overall quality of the processed sequence with respect to the original (reference) sequence. The test is divided into multiple sessions and each session should not last more than 30 minutes. For every session, several dummy sequences are added, which are used to train the human subjects and are not included in the final score. The subjects score the processed video sequence on a scale (usually 5 or 9) corresponding to their mental measure of the quality – this is termed Mean Observer Score (MOS).

When the MOS score is on a 1 to 5 scale, the scores are

1. Unacceptable
2. Poor
3. Fair
4. Good
5. Excellent

The results can, of course, vary from test to test, but if the pool is large enough (16 or more), the scores tend to stabilize.

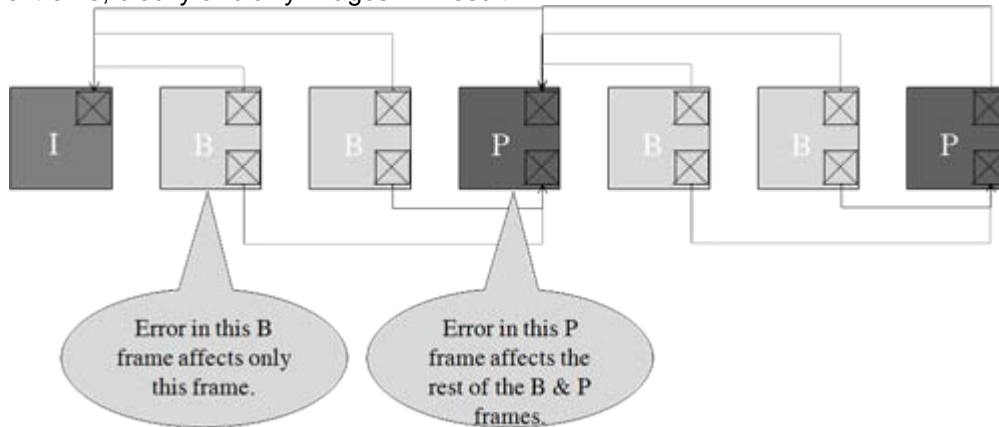
## Types of Errors

Two types of problems can arise with digital television:

- The digital transmission path can fall below acceptable levels and cause a complete loss – i.e. no picture and no audio.
- The amount and quality of the compression can lend itself to poor quality.

Checking digital transmission paths for errors is fairly straight forward. Sending a known signal and verifying that the received path is a bit-for-bit match.

Many video CODECs use a Group of Pictures (GoP) frame structure, which consists of independently coded reference frames (“I” frames), motion changes from the last reference frame (“P” frames) and motion changes from the last reference or next reference frame (“B” frames). If a transmission error occurs, the type of frame lost determines the propagation time of the error. If the compression is too extreme, blocky or blurry images will result.



Most audio CODECs detect high frequency components and encode these with very few bits because the human ear can only hear loud high frequencies. Some algorithms reduce the dynamic range to reduce the amount of data. If a transmission error occurs, the audio will pop or go silent. If the compression is too extreme, the audio will lack depth – i.e. sound tinny or hollow.

## Objective Testing

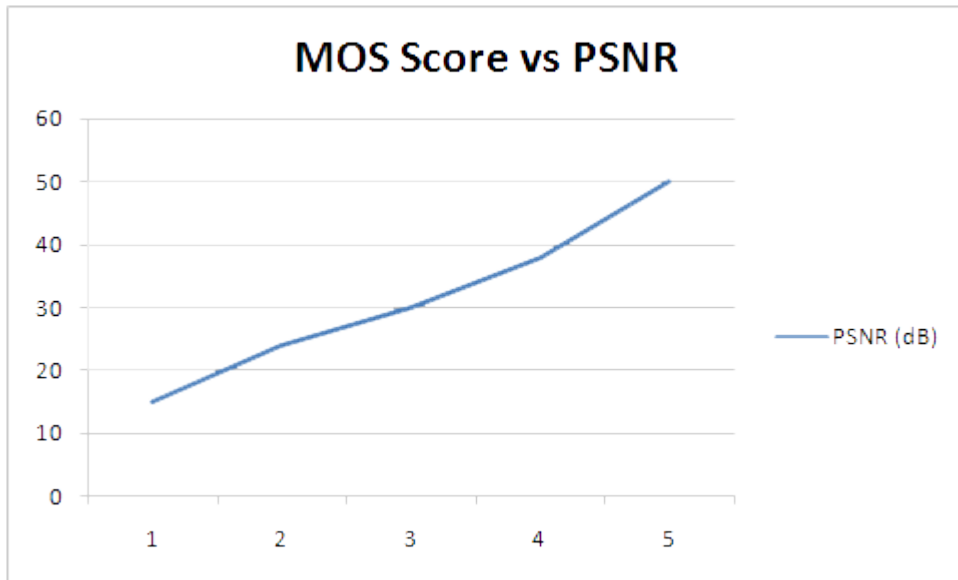
A number of algorithms have been developed to estimate video quality. These algorithms are then fit to the subjective data, which ideally reflects an objective way to measure subjective quality. The algorithms are divided into 3 general types:

- Full reference algorithms compare the output video stream to its input (or to another point)
- No reference algorithms analyze on the output stream
- Reduced reference algorithms extra specific information from the input stream and use it when analyzing the output stream.

For this paper, we will confine our discussion to full reference algorithms.

To start, the 2 streams (“reference” and “processed”) must be aligned both temporally and spatially. Audio and Video synchronization issues are reported at this point. Regardless, of whether the audio and video are in-sync or not, both signals can be further analyzed.

The most widely used metrics are PSNR (Peak Signal-to-Noise Ratio) or MSE (Mean Squared Error). Both measure the mean error between input and output. PSNR expresses the result as a ratio of the peak signal expressed in dB. PSNR and MSE are known as a dreadful video quality predictor, but they do serve an important role. Unlike the indices soon to be discussed, PSNR and MSE are metrics. They measure the absolute difference between two signals, which is completely quantifiable. This is very important in QA and Monitoring where the perceived quality has already been measured in the laboratory environment and what is needed is PASS/FAIL indicator. A PSNR value of 35dB is generally considered good. A general comparison of PSNR to MOS is shown below.



Traditional perceptual video quality index methods are based on a bottom-up approach which attempts to simulate the functionality of the relevant early human visual system (HVS) and human audio systems (HAS) components. These methods usually involve

- Video/Audio alignment
- Low pass filtering (to simulate the eye – video only)
- Calculating the differences that affect the human eye/ear.
  - Blockiness
  - Blurriness
  - Noise
  - Lack of Dynamic Range
  - Loss of High Frequencies.
- Classify the types of distortions.
- Generate a number.

This number should increase (or decrease) when the video quality increases and decrease (increase) when the video quality decreases.

While these bottom-up approaches can conveniently make use of many known psychophysical features of the HVS/HAS, it is important to recognize their limitations. In particular, the HVS and HAS are complex and highly non-linear systems and the complexity of natural images/sounds are also very significant, but most models are based on linear or quasi-linear operators that have been characterized using restricted and simplistic stimuli. Some models that fit into this category are listed below:

- Sarnoff/PQR – First Widely Heralded HVS Metric
- VQM – Video Quality Metric
- PEVQ – Perceptual Evaluation of Video Quality
- PEAQ – Perceptual Evaluation of Audio Quality

The structural similarity approach provides an alternative and complementary way to tackle the problem of video quality assessment. It is based on a top-down assumption that the HVS is highly adapted for extracting structural information from the scene, and therefore a measure of structural similarity should be a good approximation of perceived image quality. The idea is that the eye can recognize a shape even if part of it is missing. It has been shown that a simple implementation of structural similarity (SSIM) outperforms state-of-the-art perceptual image quality metrics. However, the SSIM index achieves the best performance when applied at an appropriate scale (i.e. viewer

distance/screen height). Calibrating the parameters, such as viewing distance and picture resolution, create the most challenges of this approach. To rectify this, multi-scale, structure similarity (MS-SSIM) has been defined. In MS-SSIM, the picture is evaluated at various resolutions and the result is an average of these calibrated steps. It has been shown that MS-SSIM out-performs simple SSIM even when the SSIM is correctly calibrated to the environment and dataset.

In either the top down or bottom up approach, the model produces a number and that number needs to be correlated with the subjective MOS. Three (3) methods exist for this:

- Differential Mean Opinion Score (DMOS)
- Mean Opinion Score (MOS)
- Just Noticeable Differences (JND)

Many people prefer the simpler MOS (actually, DMOS as it is the difference between “reference” and “processed” Mean Opinion Score). A group of people are asked to rate a video sequence relative to reference (full reference). The general methodology for conducting subjective tests is outlined in ITU-R BT.500. The measurement gives a numeric value based on a 1-5 scale. The ITU recommends MOS (or DMOS) under ITU-T P.910. The heuristic, nominal values for MOS are listed below:

- 4.4-5.0 – Very Satisfied
- 4.0-4.3 – Satisfied
- 3.0-3.9 – Some Users Satisfied
- 2.0-2.9 – Many Users Dissatisfied
- 1.0-1.9 – Most Users Dissatisfied

JND reports how many users need to be put into a room before 1 person thinks that the “reference” video quality is better and 1 person thinks that the “processed” video quality is better. The score is written as  $\text{NumberOfPeople} = 2(\text{JND}+1)$ . This method is the foundation for T1.TR.75.2001 (“Objective Perceptual Video Quality Measurement Using a JND-Based Full Reference Technique”).

JND Score	Experts	Percentage	Description
0	2	50%	If you ask 2 experts which video is better, they cannot agree.
1	4	75%	3 pick one sequence and 1 picks the other sequence
2	8	87.5%	7 pick one sequence and 1 picks the other sequence
3	16	93.75%	
4	32	96.875%	
5	64	98.437%	
6	128	99.219%	
9	1024	99.902%	1023 pick one sequence and 1 picks the other sequence

Since the JND and DMOS algorithms use different philosophical approaches, there is no direct correlation between them. In general, we see the following behavior. Please remember that JND calculates the blockiness and blurriness of an image; while DMOS calculates whether structures are still the same shape.

DMOS	JND	Description
	13+	Probably not aligned check Spatial and Temporal Alignment
4-3.5	10.0-12.99	Unwatchable
3.4999-3.0	7.0-9.99	Annoying
2.9999-0.4	2.0-6.99	Broadcast Quality
0.3999-0.0001	0.01-1.99	Production Quality
0	0	No Defects

## Subjective Data

The most important item to remember is that lossy, compressed signals have distortions. To understand quality, we must correlate metrics or indices to subjective MOS data. To this end, we must have an open, searchable database of subjective data.

The VQEG (Video Quality Experts Group) created a large database of video. They compressed these using H.263, H.264, and MPEG-2 and conducted subjective tests. These databases are open to member companies, but are not royalty free.

The University of Texas started with 10 royalty free videos from the Technical University of Munich and distorted these in many ways using MPEG-2 and H.264 and transmitted them over IP networks. They conducted subjective tests and are in the process of releasing their database called LIVE along with the royalty free data.

## Video Clarity ClearView Solution

Video Clarity defined 2 product lines the ClearView Video Analysis and RTM (Real Time Monitor).

RTM captures 2 live inputs, aligns the audio and video inputs, reports lip-sync issues, calculates the absolute difference between the 2 inputs (metric), continually reports the quality score, generates a pass/fail, and saves failures for further offline analysis.

ClearView Video Analysis generates test signals, captures live inputs, and inputs compressed or uncompressed files. It then aligns the audio and video and reports lip-sync issues. It calculates the DMOS, JND, and/or PSNR scores. It uses the Sarnoff/PQR algorithm ported to JND (using the VQEG database) and the MS-SSIM algorithm ported to DMOS (using the University of Texas' LIVE database). It also lets you view the "reference" and "processed" signals side-by-side or their difference maps for your own subjective evaluation.

The Sarnoff and MS-SSIM algorithms are further discussed on our website at [www.videoclarity.com/WhitePapers.html](http://www.videoclarity.com/WhitePapers.html).

## The Author

Bill Reckwerdt has been involved in digital video since the early 90's from digital compression, video on demand, to streaming servers. He received his MS specializing in Behavioral Modeling and Design Automation from the University of Illinois Urbana-Champaign.

He is currently the VP of Marketing and the CTO for Video Clarity, which makes quantitative, repeatable video quality testing tools. For more information about Video Clarity, please visit their website at <http://www.videoclarity.com>.