Crowdsourced Estimation of Collective Just Noticeable Difference for Compressed Video with the Flicker Test and QUEST+

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***Abstract*—The concept of videowise just noticeable difference (JND) was recently proposed for determining the lowest bitrate at which a source video can be compressed without perceptible quality loss with a given probability. This bitrate is usually obtained from estimates of the satisfied used ratio (SUR) at different encoding quality parameters. The SUR is the probability that the distortion corresponding to the quality parameter is not noticeable. Commonly, the SUR is computed experimentally by estimating the subjective JND threshold of each subject using a binary search, fitting a distribution model to the collected data, and creating the complementary cumulative distribution function of the distribution. The subjective tests consist of paired comparisons between the source video and compressed versions. However, as shown in this paper, this approach typically overestimates or underestimates the SUR. To address this shortcoming, we directly estimate the SUR function by considering the entire population as a collective observer. In our method, the subject for each paired comparison is randomly chosen, and a state-of-the-art Bayesian adaptive psychometric method (QUEST+) is used to select the compressed video in the paired comparison. Our simulations show that this collective method yields more accurate SUR results using fewer comparisons than traditional methods. We also perform a subjective experiment to assess the JND and SUR for compressed video. In the paired comparisons, we apply a flicker test that compares a video interleaving the source video and its compressed version with the source video. Analysis of the subjective data reveals that the flicker test provides, on average, greater sensitivity and precision in the assessment of the JND threshold than does the usual test, which compares compressed versions with the source video. Using crowdsourcing and the proposed approach, we build a JND dataset for 45 source video sequences that are encoded with both advanced video coding (AVC) and versatile video coding (VVC) at all available quantization parameters. Our dataset and the source code have been made publicly available at http://database.mmsp-kn.de/flickervidset-database.html.**

***Index Terms*—Just noticeable difference, psychometric function, satisfied user ratio, flicker test, subjective quality assessment, Bayesian adaptive psychometric testing method, AVC, VVC.**

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project ID 496858717, titled "JND-based perceptual video quality analysis and modeling" and Project ID 251654672 – TRR 161 (Project A05). This research was also kindly supported by the Zukunftskolleg, the University of Konstanz, with funding from the Excellence Strategy of the German Federal and State Governments.

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I. Introduction

COMPRESSION is the main tool used to achieve the target video bitrates required to meet transmission bandwidth and storage constraints. However, as the bitrate decreases, additional compression artifacts are introduced. These artifacts eventually become noticeable and even annoying to human consumers. Therefore, methods for assessing video quality are being explored to determine the lowest bitrate at which the video content provider deems the perceived visual quality appropriate for delivery.

Within high-quality media streaming, the following tasks are challenging in automatic video quality assessment [1]: (1) Performing quality assurance for the re-encodings of media submitted by the original producers, (2) quality monitoring of the delivered video sequences to characterize the general satisfaction requirements of subscribers, (3) optimizing encoding parameters such that the bitrate is minimized for each targeted visual quality level, (4) optimizing streaming bitrate selection based on the speed of the consumer's network and the perceptual qualities of the upcoming video segments within a specified time fram, and (5) evaluating codec and processing technology to help select and update the methods for deployment that yield the best perceptual qualities.

Consumers of streaming applications pay for services and expect to receive content without any annoying impairments. Thus, in this context, only the top quality levels of streaming around the near-lossless range are relevant. To provide fine granularity for such high-quality stimuli, a new evaluation approach was introduced based on the concept of just noticeable difference (JND). The JND was introduced by the 19th-century psychologist Ernst Weber, who defined it as the "minimum amount by which stimulus intensity must be changed in order to produce a noticeable variation in sensory experience".

Without loss of generality, let us consider a video codec parameterized by a distortion level $x \in [0, 1]$. When $x = 0$, the coding is lossless; i.e., the reconstructed video is identical to the source, so no distortion occurs. However, as x increases, the bitrate of the compressed video decreases, which increases the likelihood that the distortions can be perceived. Thus, when a video is compressed, the smallest distortion level x at which an observer can perceive visual distortion is the JND.

However, physiological and visual attention mechanisms vary and involve many subjective factors, and the JND depends on such indeterminate circumstances. In mathematical terms, the JND is a random variable. A discrete random variable

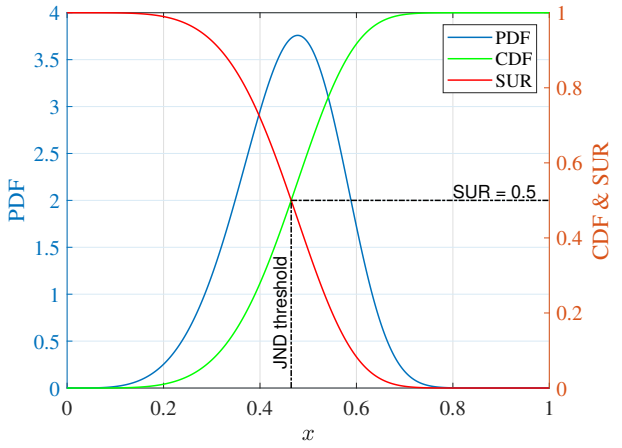


Fig. 1: The probability density function (PDF), cumulative distribution function (CDF) or psychometric function, and SUR function for a continuous JND random variable. The JND threshold is the distortion level where the psychometric function is equal to 1/2.

is characterized by its probability distribution function, and a continuous random variable is characterized by its probability density function. When a number is specified for the JND, this number is typically the JND threshold. This threshold is the smallest distortion level at which an observer will notice a degradation in quality with a probability of 1/2.

The cumulative distribution function of the JND random variable is a monotonically increasing function that specifies the probability of an observer detecting distortion at each distortion level. In psychophysics, this function is called the psychometric function for the JND, and its graph is typically an S-shaped curve (Fig. 1).

For a whole population of subjects, the satisfied user ratio (SUR) denotes the probability that a randomly selected subject will not notice any distortion artifacts when comparing a source video with its compressed version at a given distortion level. Therefore, the SUR is also a function of the distortion level and is given by the complementary cumulative distribution function of the JND random variables averaged over all subjects in the population. Modeling the SUR can help content providers minimize transmission costs while guaranteeing user satisfaction for any target proportion of their customers.

Since 2015, datasets of videos annotated with JND measurements have been created [2], [3], [4], [5]. These works apply a three-stage method: (1) For a given source stimulus and all participants in a study, the individual JND thresholds are estimated. (2) A distribution model is fitted to the threshold data. (3) The complementary cumulative distribution function is taken as an estimate of the SUR curve.

This procedure models the individual psychometric functions as Heaviside step functions, where each function exhibits a discontinuous jump at the individual JND threshold. However, this simplification cannot account for the expected occurrences of distortion detection at subthreshold distortion parameters. Consequently, the SUR yielded by this method may be overestimated at subthreshold parameters. When applied in a system for rate control, such an overestimation would make compression artifacts visible to a larger amount of the viewer population than anticipated.

Rather than estimating JND thresholds, complete psychometric functions must be estimated to derive SUR curves accurately. Various psychometric function models identify the probability of detecting distortion from the underlying sensory mechanism, presented as a parameterized function of the distortion level [6].

To estimate the SUR, one could use an adaptive psychometric method to sequentially estimate the cumulative JND distributions of many subjects and then average these estimates. A key contribution of our paper is the proposal of an alternative approach. We regard the entire population as a collective observer and apply QUEST+ [7], a state-of-the-art Bayesian adaptive psychometric method, to directly estimate the psychometric function. This method can be implemented by choosing a new random observer for each trial of the adaptive method. We demonstrate by simulation that this approach is more efficient than estimating and averaging the individual JND distributions of the subjects.

Another contribution of our paper is the application of the flicker test for video JND detection. In 2014, the flicker test was introduced [8] for comparing source images and distorted versions. In this method, the test image is temporally interleaved with its source, and artifacts in the test image may appear to the viewer as a flicker effect. In the experiments, the flickering image is randomly displayed on the left or right side, and the source image is displayed on the other side. The test subjects must identify which side they observe a flicker effect on.

We show that the flicker test can also be applied for video quality assessment in the near-lossless quality range. The flicker test provides increased sensitivity to distortion in the human visual system. Moreover, it yields more precise results than the plain test, i.e., side-by-side comparisons between a distorted video sequence and its source.

Evaluating video quality in controlled and standardized lab experiments is often time-consuming and may not fully encompass the viewing conditions experienced in real-world settings. In contrast, crowdsourcing experiments provide various advantages, including a diverse participant pool, realistic hardware setups, and viewing environments that resemble those of typical users [9], [10]. Recent research [9], [10], [11], [12], [13] has shown that video quality ratings obtained through crowdsourcing are comparable to those obtained in laboratory settings.

In [14], a large JND-based dataset of JPEG and BPG compressed images was generated by crowdsourcing experiments. In this paper, we use crowdsourcing and a flicker test to construct a JND dataset for compressed videos.

Developing models for accurately predicting the visual quality of compressed videos is an ongoing challenge. Examples of these models include [15], [16], [17], [18] for the prediction of mean opinion scores and [19], [20], [21], [22], [23], [24], [25], [26] for the prediction of the JND and the SUR, respectively.

The most successful approaches are those based on machine learning, especially deep learning. However, deep learning is data hungry, and video JND datasets are lacking in size and quality. All the existing video JND datasets were produced in laboratory studies. In these studies, individual JNDs were

obtained through binary search, which is time-consuming. This severely limited the number of video sequences and their JNDs in previous datasets. The data in some previous studies are also inconsistent, showing very large intersubject variability. Therefore, as noted in recent papers [25], [27], [19], larger and more consistent JND datasets are needed. Such datasets are essential for advancing state-of-the-art video JND prediction methods, especially those based on deep learning models.

Our paper makes four main contributions to help build large and reliable video JND datasets.

- We show that the common approach of estimating the SUR function from the distribution of individual JND thresholds of a group of subjects causes bias that may lead to an overestimation or underestimation of the SUR.
- We propose a new method for SUR estimation. In our method, which we call the collective observer method, we randomly select subjects to collect responses for paired comparisons. The distortion level for each paired comparison is determined using an adaptive psychometric testing procedure (QUEST+ [7]). We show via simulations that our method estimates the SUR more accurately and efficiently than does the traditional approach.
- We use a flicker test to estimate the JND in encoded video sequences. Our experimental results show that the flicker test increases the sensitivity and precision of the JND threshold estimation.
- We conduct a within-subjects study to compare the estimated SUR using the flicker and plain tests. We use the proposed QUEST+-based method for estimating collective psychometric functions, along with the flicker test and crowdsourcing, to construct a dataset comprising 45 source videos. The videos are encoded with advanced video coding (AVC, H.264, MPEG-4 Part 10) [28], [29] and versatile video coding (VVC, H.266, MPEG-I Part 3) [30], [31].

The remainder of this paper is organized as follows. Section II presents the state-of-the-art research related to our contributions. We review the past attempts to estimate JND thresholds, fitted distributions, and corresponding SUR curves. Then, we review the past work on the flicker test and present an overview of the current JND-based video quality sets. Section III provides formal definitions of the main terminology, such as the individual and collective JND, their thresholds, psychometric functions, and the SUR. For Gaussian models of the JND, we show that a percentile of JND thresholds in an observer population is an overestimate of the SUR at subthreshold distortion parameters. We introduce the concept of the collective observer and show by simulation that this approach is a more efficient method for estimating the collective psychometric function than averaging a set of individual JND distributions. Section IV describes how the flicker test is adapted for video quality assessment. Section V describes how to crowdsource JNDs for videos. Section VI compares the efficiency of the flicker test with that of conventional paired comparisons. This comparison is done through a crowdsourcing experiment using a within-subject study design, where the SUR curves were estimated with the proposed QUEST+-based method.

II. Related work

In this section, we review the state-of-the-art studies concerning the following main contributions of the paper: JND and SUR estimation, flicker tests for quality assessment, and construction of video-based JND datasets.

A. JND and SUR estimation

In previous JND studies [32], [33], [4], [3], [34], [35], [36], [37], [14], the SUR function is built by aggregating the psychometric functions of a group of subjects. Each subject's psychometric function is estimated as a Heaviside function exhibiting a step at the JND threshold and neglecting the subject's uncertainty in determining the JND. A paired comparison is typically used to estimate the JND threshold for a given subject. For example, when comparing a pair of videos, a high-quality source video and a distorted version are played side-by-side or sequentially. The subject indicates which video is of lower or higher quality depending on the subjective test question. In principle, the source video should be compared to the whole set of distorted versions. However, in practice, the search for the JND threshold is accelerated with binary search [5], [2], [4] or relaxed binary search [3].

Note that modern psychophysics approaches [38], [39], such as signal detection theory, argue that the observed JND is not an absolute quantity but depends on motivational and perceptual parameters. Thus, the JND for a given individual is a statistical quantity rather than an exact quantity. We show in Section III that this implies that fitting a distribution to the obtained JND thresholds does not properly represent the overall, population-wide JND distribution and may result in an overestimation of the SUR. Furthermore, we propose a solution to this limitation.

B. Flicker test for quality assessment

The flicker test was introduced by Hoffman and Stolitzka in 2014 [8] for image quality assessment to increase the sensitivity of the human visual system in detecting image artifacts in near-lossless image compression. The method was shown to be effective and was subsequently adopted by the JPEG AIC standard [40].

Men et al. [41] showed that the flicker test provides greater sensitivity for reconstructing impairment scales of distorted images than the plain test. Furthermore, the flicker test achieved the same correlation with ground truth scores with a smaller number of required paired comparisons than the plain test. In [37], the flicker test was used for subjective picturewise JND assessment to compare a slider-based method, a keystroke-based method, and the paired comparison with the relaxed binary search method. The flicker test was shown to provide about twice the sensitivity of a conventional side-by-side comparison for estimating the JND for JPEG compressed images. We attribute the strengths of the flicker test as compared to the conventional side-by-side comparison to the reduced visual short-term memory required to make a judgment [42] and to the high sensitivity of the human visual system in detecting temporal contrast [43]. In [14], the flicker test was used in large-scale crowdsourcing experiments to determine the JND for JPEG and BPG compressed images.

TABLE I: Comparison of the state-of-the-art JND-based video quality datasets

Datasets	Lin *et al.* [5]	MCL-JCV [2]	Huang *et al.* [4]	VideoSet [3]	our dataset
Publication year	2015	2016	2017	2017	2022
Number of source videos	5	30	40	220	45
Resolution of source videos	1920×1080	1920×1080	1920×1080	1920×1080[a]	640×480
Distortion type	AVC/HEVC	AVC	HEVC	AVC	AVC/VVC
Distortion levels per each stimulus	51/51	51	51	51	51/63
Test environment	lab	lab	lab	lab	online
Subjective assessment method	PC[b]	PC[b]	PC[c]	PC[b]	FT[d]/PC[c]
Search algorithm	binary search	binary search	binary search	relaxed binary search	QUEST+

[a] Three lower resolutions of the same video were used: 1280×720, 960×540, and 640×360.
[b] Paired comparison (PC): the two videos are displayed sequentially.
[c] PC: the two videos are displayed side-by-side.
[d] Flicker test (FT): a high quality source video and a flickering version are displayed side-by-side. Subjects determine which video is flickering.

The first attempts to extend the flicker test to video sequences were briefly mentioned in [44]. The results were not regarded as promising, but no detailed information was given. In [40], the flicker test was not included for video quality assessment in the JPEG XS standard because motion could mask the flicker, an effect called motion silencing.

In this paper, we revisit and examine the use of the flicker test for video quality assessment in a crowdsourcing study.

C. JND-based video quality datasets

The current JND datasets [2], [5], [4], [3] for compressed video differ in the number of source videos, resolution, compression type, subjective assessment method, and search algorithm. Table I summarizes these datasets. In this subsection, we briefly describe how each dataset was built.

The study by Lin *et al.* [5] involved five video sequences of resolution 1920×1080. The videos were displayed on a 65-inch TV with a resolution of 3840×2160. The viewing distance was 2 m from the center of the monitor. The video sequences were encoded with AVC and high-efficiency video coding (HEVC). The video sequences were compressed by varying the value of the quantization parameter (QP) of the video codec from 1 to 51. A subjective study was also conducted to determine the number of quality levels that a subject could distinguish. A bisection search method was used to identify these quality levels. In this search, two videos were displayed sequentially, and the subject assessed whether these videos were noticeably different. Twenty subjects participated in the study.

Wang *et al.* [2] considered 30 source video sequences. More than 150 people participated in the study. JND samples were collected from 50 subjects. The other settings were the same as those in [5]. The resulting JND dataset was called MCL-JCV.

Huang *et al.* [4] generated a JND-based dataset for HEVC. The dataset contains 40 high-definition (HD) source video clips with a frame rate of 30 fps and a duration of 5 s. All source videos were encoded using HM 16.0 HEVC reference software, with QP values ranging from 0 to 51. To estimate the JND threshold for each source and its 51 encoded versions, a subjective test was conducted with 30 subjects. The source video and an encoded version were played side-by-side time-synchronously on a 65-inch 4K UHD TV display in a laboratory environment. The standard binary search was used to accelerate the search for the JND threshold. Outliers were excluded according to the three-sigma rule.

Wang *et al.* [3] built a large-scale JND video dataset called VideoSet for 220 source videos of 5 s at four resolutions (1080p, 720p, 540p, 360p). Each source video was compressed with AVC using QP values ranging from 1 to 51. The viewing distance was set according to the ITU-R BT.2022 recommendation. The source video and a distorted version were displayed sequentially. A relaxed binary search was used to estimate the personal JND threshold for each subject. At least 30 subjects were involved in the JND estimation for each video sequence. Data from unreliable subjects and outliers were removed.

All of the current video JND datasets were built in laboratory experiments and are limited in size.

III. The collective psychometric function

In this section, we first formally define the collective psychometric function underlying the SUR curve by adapting the notations from [45]. Then, we focus on estimating the SUR. In particular, we show through simulations that directly estimating the collective psychometric function is more efficient than averaging individually estimated psychometric functions.

A. Definitions

The psychometric function models the relationship between the level of distortion of the stimulus and an observer's performance in detecting the distortion or discriminating between the distorted stimulus and the source stimulus. The SUR assumes a total population of observers and estimates the proportion of those who cannot detect the distortion.

We consider a lossy image or video compression scheme that produces monotonically increasing distortion magnitudes. The distortion depends on an encoding parameter that can take only a finite number of values. For example, for AVC and VVC, we use QP to control the quality of the encoded video. The range of QP values is $1, \ldots, 51$ for AVC and $1, \ldots, 63$ for VVC. Increasing the QP decreases the bitrate and reduces the visual quality.

Definition 1 (Individual JND). For a given observer and a pristine source stimulus $S[0]$, we associate distorted stimuli $S[n],\ n = 1, \ldots, N$ corresponding to distortion levels

$n = 1, \ldots, N$. The *individual just noticeable difference*, which we denote by JND, is a random variable whose value is the smallest distortion level n that can be perceived by the observer when the stimulus $S[n]$ is compared to the source stimulus $S[0]$.

We interpret this model in the context of the detection task by evaluating a test stimulus at distortion level n with respect to the corresponding source. According to the above definition, the observer detects the distortion in the test stimulus with the probability that JND $\leq n$. Equivalently, the observer notices the distortion if a randomly drawn sample of JND has a value less than or equal to n.

In a paired comparison in the 2-alternative forced-choice (2AFC) setting, the two stimuli are presented in random order, and the task is to identify the stimulus with distortion. In this case, an attentive observer will identify the distorted stimulus with probability $\frac{1}{2} + \frac{1}{2}\text{Prob(JND} \leq n)$.

To define the SUR, we consider a population of observers, each of whom has an individual JND distribution.

Definition 2 (Collective JND). Assume a population of observers and a pristine source stimulus $S[0]$ with distorted stimuli $S[n],\ n = 1, \ldots, N$. The *collective just noticeable difference*, which we denote by JND, is a random variable whose value is the smallest distortion level n that can be perceived by a random observer of the population when the stimulus $S[n]$ is compared to the source stimulus $S[0]$.

For a finite population of observers, the distribution of the collective JND is just the average of the distributions of the individual JNDs of all observers.

Definition 3 (JND threshold). The median of the individual (resp. collective) JND random variable is called the individual (resp. collective) *JND threshold*.

Definition 4 (Psychometric functions and SUR). The *individual and collective psychometric functions associated with the JND* are the cumulative distribution functions of the corresponding JND random variables. The SUR is the complementary cumulative distribution function of the collective JND random variable.

In the above definitions, discrete distortion levels $n = 1, \ldots, N$ are used, which are applicable for the main application, i.e., JND-based quality assessment of compressed video sequences. However, these definitions can be easily adapted and applied for continuous distortion levels, such as additive Gaussian noise, parameterized by the noise amplitude as the distortion level. In the next subsection, for simplicity of notation, we assume that the distortion level is continuous.

B. Analysis of common SUR estimation

In previous work, the SUR was estimated by the complementary cumulative distribution function of a set of estimated individual JND thresholds. Several sources of error may affect the estimation accuracy. (1) The sample of JND thresholds may stem from a set of subjects that is not representative of the population, (2) JND thresholds estimated by approximation methods such as the bisection method may be inaccurate, and (3) the fitting procedure for approximating the distribution of JND thresholds may introduce errors.

Even if we could eliminate these error sources, the traditional method would still exhibit systematic bias in the SUR estimation, as shown by the following proposition.

Proposition 1. *Assume that the individual JND random variables are normally distributed with variance σ^2 and that the individual JND thresholds are normally distributed with mean $\bar{\mu}$ and variance σ_0^2. Then, the complementary cumulative distribution function of the individual JND thresholds overestimates the SUR for all distortion levels smaller than $\bar{\mu}$ and underestimates it for all distortion levels greater than $\bar{\mu}$.*

Proof. Let $\widehat{\text{SUR}}(x)$ denote the estimate of the satisfied user ratio at x given by the complementary cumulative distribution function of the individual JND thresholds. We have

$$\begin{aligned} \widehat{\text{SUR}}(x) &= \int_x^\infty \phi_{\bar{\mu},\sigma_0^2}(\mu)\, d\mu \\ &= 1 - \Phi\left(\frac{x-\bar{\mu}}{\sigma_0}\right) \end{aligned} \tag{1}$$

where ϕ_{a,b^2} denotes the probability density function of the normal distribution with mean a and variance b^2, and Φ is the cumulative distribution function corresponding to $\phi_{0,1}$.

Let $f(s)$ denote the probability density function of the collective JND random variable at distortion level s. From Definition 2, we have $f(s) = E[\phi_{M,\sigma^2}(s)]$, where E denotes the expectation operator and M is the random variable representing the mean μ of the JND of a random observer. Thus,

$$f(s) = \int_{-\infty}^\infty \phi_{\mu,\sigma^2}(s)\phi_{\bar{\mu},\sigma_0^2}(\mu)\, d\mu. \tag{2}$$

Noting that $\phi_{\mu,\sigma^2}(s) = \phi_{0,\sigma^2}(s-\mu)$ and that the convolution of two Gaussians is Gaussian, we obtain

$$\begin{aligned} f(s) &= \int_{-\infty}^\infty \phi_{0,\sigma^2}(s-\mu)\phi_{\bar{\mu},\sigma_0^2}(\mu)\, d\mu \\ &= (\phi_{0,\sigma^2} * \phi_{\bar{\mu},\sigma_0^2})(s) \\ &= \phi_{\bar{\mu},\sigma^2+\sigma_0^2}(s). \end{aligned} \tag{3}$$

The SUR at distortion level x is the complementary cumulative distribution function of $f(s)$,

$$\begin{aligned} \text{SUR}(x) &= \int_x^\infty \phi_{\bar{\mu},\sigma^2+\sigma_0^2}(s)\, ds \\ &= 1 - \Phi\left(\frac{x-\bar{\mu}}{\sqrt{\sigma^2+\sigma_0^2}}\right). \end{aligned} \tag{4}$$

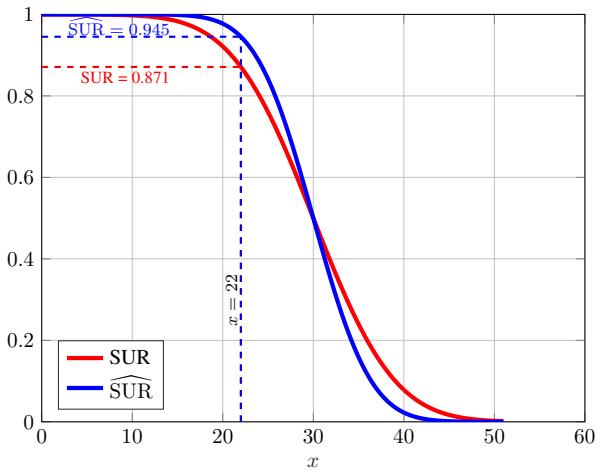


Fig. 2: Comparing the SUR curve of the collective JND distribution with its estimate using the common approach as discussed in Section III-B. In this plot, for the collective JND random variable X, we assumed that each observer i had a JND random variable $X_i \sim \mathcal{N}(\mu_i, 5)$ where $\mu_i \sim \mathcal{N}(30, 25)$.

If $x < \bar{\mu}$, then $(x - \bar{\mu})/\sqrt{\sigma^2 + \sigma_0^2} > (x - \bar{\mu})/\sigma_0$. Since Φ is strictly increasing, (1) and (4) yield $\widehat{\text{SUR}}(x) > \text{SUR}(x)$. Similarly, if $x > \bar{\mu}$, then $\widehat{\text{SUR}}(x) < \text{SUR}(x)$. □

The SUR accounts for the variance σ^2 of the individual JND distributions, which is ignored by the estimate $\widehat{\text{SUR}}(x)$.

Using an example from the VideoSet data [3], we estimated the parameters $\bar{\mu}$ and σ_0 as 30 and 5, respectively. If we assume that all participants have $\sigma = 5$, then for $x = 22 < \bar{\mu}$, we obtain the true value $\text{SUR}(x) = 0.871$. This is overestimated, as $\widehat{\text{SUR}}(x) = 0.945$ as shown in Fig. 2.

In summary, we have conducted a mathematical analysis of a general model of a population of observers. This analysis considered normal distribution functions of the individual JND random variables with different means and equal variances. Our results prove that fitting a distribution model to JND thresholds may lead to SUR overestimation or underestimation.

When the SUR is overestimated, media are transmitted at overly strong compression levels. The fraction of viewers who notice compression artifacts will be larger than anticipated. Similarly, when the SUR is underestimated, media are transmitted at higher bitrates than necessary. Our analysis will help to prevent such undesirable effects in practical applications.

C. The collective observer

To overcome the above limitations of the common method of SUR estimation, one should compute the collective JND distribution from the average of all individual JND distributions rather than from the individual JND thresholds alone. For this purpose, each participant in an empirical study could compare each source stimulus with numerous compressed versions of it and report whether a distortion was detected. This process can be implemented in various ways. From such data, individual JND distribution functions can be fitted and averaged for each source stimulus. The complementary cumulative distribution functions serve as estimates of the corresponding SUR functions. We call this approach the "average observer".

However, this approach is inefficient when the budget for comparing one source stimulus with its distorted versions is fixed. Instead, the comparisons should be conducted by many different subjects. This process is described in the following.

Definition 5 (Collective observer). A JND/SUR assessment method is called a "collective observer" if it directly estimates the collective JND distribution and the SUR function as follows. Responses to paired comparisons between distorted stimuli and the source stimulus are collected, and each response is obtained from a randomly selected observer. The collective JND distribution function is estimated by applying a fitting procedure to the collected responses.

In Subsection III-E, we present simulations that compare the accuracy, precision, and efficiency of the collective and average observer, as well as the traditional SUR estimation method.

D. Modeling and estimation of the psychometric function

Psychometric functions for detection tasks such as the one considered here are often modeled by S-shaped cumulative distribution functions $F(x; \alpha, \beta)$, where α and β are related to the threshold and the slope at the threshold, respectively. For example, in this section, we use the Gaussian CDF

$$F(x; \alpha, \beta) = \Phi\left(\frac{x - \alpha}{\beta}\right). \tag{5}$$

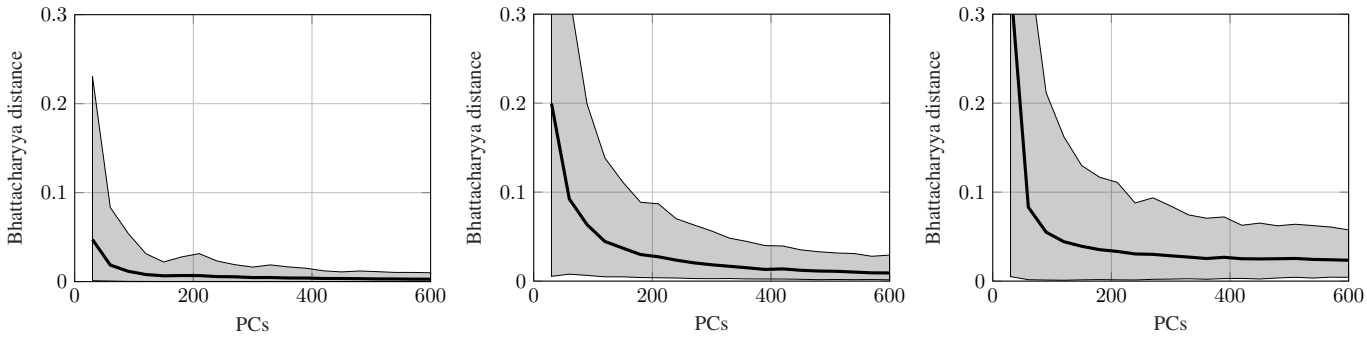
In psychophysics, it is common practice to use 2AFC questions in paired comparisons for JND threshold estimation. A pristine stimulus and a distorted stimulus are presented in random order, and the distorted stimulus must be identified. Guessing will yield the correct response with a probability of 1/2. To account for this, the psychometric function w.r.t. the 2AFC setting, giving the probability of a correct response, is typically expressed as

$$\psi(x; \alpha, \beta, \lambda) = \frac{1}{2} + \left(\frac{1}{2} - \lambda\right) F(x; \alpha, \beta). \tag{6}$$

This includes a lapse rate λ, which indicates the probability that the distorted stimulus is not identified, regardless of how strong the artifacts are. The lapse rate accounts for incidents such as the observer being inattentive or the view of the stimulus being obscured. From the cumulative distribution function $F(x; \alpha, \beta)$, the SUR is obtained as $1 - F(x; \alpha, \beta)$.

Many methods exist for estimating a psychometric function empirically. Most of these methods are designed to estimate only the threshold α as this is often the most important or only parameter of interest. To quantify the SUR function, however, we need all parameters of the psychometric functions, including the slope parameter β.

Adaptive methods have been researched for several decades. In these methods, an algorithm decides the next stimulus for a paired comparison based on the observer responses for the previous comparisons. Two of the most prominent algorithms



(a) Collective observer (b) Average observer (c) Common approach

Fig. 3: Average Bhattacharyya distances of the estimated JND distributions to the ground truth for different budgets of paired comparisons derived from 1000 runs. The shaded areas represent the 95% confidence intervals.

TABLE II: Parameters of 10000 simulated observers were selected randomly from truncated normal distributions.

Parameter	Mean	Variance	Lower bound	Upper bound
Threshold α	26	36	1	51
Standard deviation β	5.5	1.12	1	10
Lapse rate λ	0.02	0.00002	0	0.04

are PEST [46] and QUEST+ [7]. In our work, we employ QUEST+, a recent Bayesian method that offers a large variety of application scenarios.

E. Comparing the collective observer with other approaches

We compared the proposed collective observer for estimating the collective psychometric function $F(x;\alpha,\beta)$ with the average observer and the common SUR estimation approach. We used a simulation to conduct this comparison because in a simulation, the ground truth collective JND distribution of a population is available, allowing us to study the accuracy and efficiency of competing methods.

1) Simulated population of observers: We generated a population of 10000 simulated observers, each represented by an individual psychometric function with a Gaussian CDF from Equation (6). Gaussian CDFs have also been used in prior research for modeling the JND [2], [3]. For each observer, we randomly selected the parameters α, β in $F(x;\alpha,\beta)$ and the lapse rate λ from the truncated normally distributed values. Table II summarizes these normal distributions.

The average of all individual psychometric functions $F(x;\alpha,\beta)$ is the ground truth collective psychometric function in our simulation. To numerically compare the estimates with the ground truth, we represented the collective psychometric function and the SUR using samples at equally spaced distortion levels $x_m = 1 + \frac{m}{100} \in [1, 51], m = 0, \ldots, 5000$.

In the following, we present the implementation details for the simulation of the collective and average observers, as well as the common estimation method. The simulations were then run with a fixed budget of n paired comparisons.

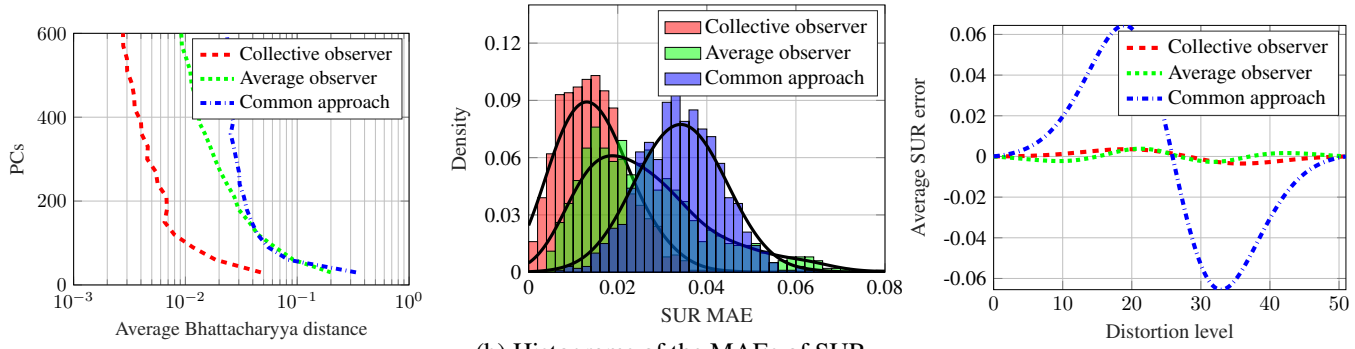
2) Collective observer: We estimated the collective psychometric function using the adaptive psychometric procedure QUEST+. We simulated 2AFC paired comparisons between distorted stimuli at levels x and the undistorted stimulus. Following the principle of the collective observer, we randomly selected one of the 10,000 observers for each comparison and evaluated the corresponding individual psychometric function (6), providing the probability of a correct response. The simulated response was then drawn according to this probability. The distortion levels for these comparisons were adaptively chosen by QUEST+ until the given budget was consumed.

3) Average observer: In the average observer method, individual psychometric functions $F(x;\alpha,\beta)$ and corresponding JND distributions for up to 20 randomly selected subjects from the population are estimated separately and then averaged. For each of the chosen subjects, the individual psychometric function was obtained by simulating 2AFC paired comparisons using QUEST+ as above; however, only the particular psychometric function $\psi(x;\alpha,\beta,\lambda)$ of the corresponding subject was applied. The number of comparisons per subject was set to 30, which is the recommended number for QUEST+ [7]. The number of subjects was determined by the given budget.

4) Common SUR estimation: The SUR function is commonly estimated using the complementary cumulative distribution of a Gaussian density function that is fitted to a set of estimated individual JND thresholds [5], [2], [4], [3]. To assess these thresholds, we considered the most recent of the above works , which proposed a relaxed binary search method. For details, see [3]. The search space for the thresholds consisted of integers ranging from 1 to 51. The number of comparisons for each threshold estimate may vary between 10 and 11. We estimated JND thresholds from randomly drawn subjects until the given budget was consumed. A Gaussian density function was fitted for the set of estimated thresholds using maximum likelihood estimation.

5) Accuracy of the estimated collective JND distribution and SUR: We compared the estimated collective JND distributions, evaluated at the chosen distortion levels x_m. The sampled values were scaled to yield probability distributions. To compare an estimated distribution with the ground truth, we computed the Bhattacharyya distance, which measures the magnitude of the difference between two probability distributions. Smaller distances indicate better approximation.

We compared the SUR function estimates using the mean absolute error (MAE), $\frac{1}{5001}\sum_{m=0}^{5000} |\widehat{\mathrm{SUR}}(x_m) - \mathrm{SUR}(x_m)|$.



(a) Number of paired comparisons needed to meet the accuracy constraint.

(b) Histograms of the MAEs of SUR estimates from 600 PCs over 51 distortion levels.

(c) Signed SUR error, averaged over all simulation runs with 600 PCs.

Fig. 4: Comparison of the collective observer, the average observer, and the common approach using 1000 simulation runs each. Shown are (a) the computational complexities of approximating the collective JND distribution, (b) the achieved mean absolute errors (MAEs) for the estimated SUR functions using 600 PCs, and (c) the bias for each method at all distortion levels using 600 PCs.

To check for the bias of the SUR estimate that is expected from Proposition 1 for the common approach, we computed the signed error at each distortion level, $\widehat{\mathrm{SUR}}(x_m) - \mathrm{SUR}(x_m)$, averaged over all simulation runs.

6) Results: After generating the simulated observers and computing the ground truth, we conducted 1000 simulation runs for each assessment method and each budget of $n = 30k$, $k = 1, \ldots, 20$ paired comparisons.

Fig. 3 shows the average Bhattacharyya distances to the ground truth distribution with 95% confidence intervals (CIs). The mean distance for the collective observer is much smaller than that of the average observer and the common approach. To better compare the efficiencies of the methods, Fig. 4a plots the number of paired comparisons required to achieve the average Bhattacharyya distance at a specified accuracy. For example, let us consider 30 individual JND thresholds as assessed in VideoSet [3]. Approximately 330 paired comparisons are required to estimate the SUR for each source video using the relaxed binary search method. In our simulation, 330 paired comparisons yielded a Bhattacharyya distance of 0.027. By employing linear interpolation of the data presented in the figure, we estimate that the collective observer would require only 51 paired comparisons to achieve the same mean distance, while the average observer would require 277.

In Figs. 4b and 4c, we study the accuracy and bias of the estimates of the SUR function. The histograms and density plots for the SUR MAE show the superiority of the collective observer regarding accuracy. Fig. 4c reveals that in the simulations, the common approach overestimates the SUR at subthreshold distortion parameters and underestimates it at suprathreshold parameters. In comparison, the magnitude of the corresponding bias of the collective and the average observers appear negligible.

In summary, we have shown via simulation that the average observer and the collective observer are bias free and approximate the collective JND and SUR functions with decreasing error when the number of paired comparisons increases. The collective observer is more efficient than the average observer. It is also much more efficient than the current state-of-the-art method. The latter uses a relaxed binary search to estimate JND thresholds, which are subsequently fitted by a Gaussian distribution.

We conclude this section by listing its main contributions.

- We provided a clear framework of definitions for individual and collective just noticeable difference.
- We showed that the current state-of-the-art method for estimating SUR curves, which involves fitting a model to JND thresholds, suffers from systematic bias. This bias leads to an overestimation at subthreshold distortion levels and an underestimation at suprathreshold distortion levels.
- We introduced a new approach for estimating the distribution of just noticeable difference and satisfied user ratio curves based on the collective observer.
- Using a large-scale simulation, we showed that the collective observer is much more accurate and efficient than the commonly used method.
- The simulation confirmed the systematic bias that was derived theoretically for the common method, whereas the collective observer hardly exhibited this bias.

IV. Flicker test for videowise JND assessment

In this section, we describe how we adapted the flicker test for JND-based video quality assessment. Additionally, we explain how we re-encoded the videos for transmission to the users' computers in the crowdsourcing experiment.

A. Test videos

1) Encoding source video sequences: We selected 45 source videos with diverse content from VideoSet [3]. The source video clips have a duration of 5 s, a spatial resolution of 1920×1080 pixels (full high-definition resolution), frame rates of 24 and 30 fps, and the color format YUV420p. The videos do not include audio.

For encoding with H.264/AVC, we used FFmpeg with the libx264 implementation of H.264/AVC with the "high" profile.

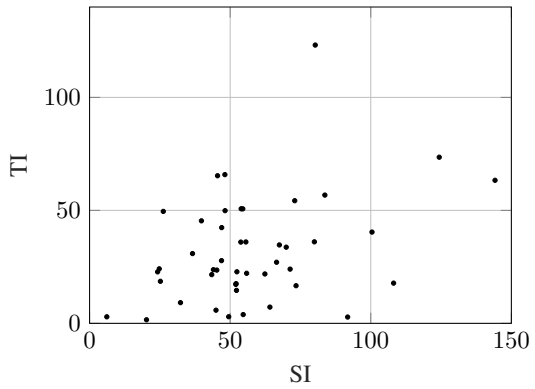


Fig. 5: TI vs. SI of the 45 source videos.

We disabled adaptive scene cut detection, used the quantization parameter (QP) as the primary bit rate control method with QP $= 1, \ldots, 51$, disabled adaptive quantization, and set the GOP size to the frame rate of the input video (24 or 30).

For encoding with H.266/VVC, we used Fraunhofer Versatile Video Encoder (VVenC) software with the expert mode encoder (vvencFFapp) implementation of H.266/VVC [47]. We applied the "medium" preset, QP $= 1, \ldots, 63$, disabled adaptive quantization, and set an intraframe period of length 64.

Fig. 5 illustrates the diversity of the 45 selected cropped source videos by plotting temporal information (TI) against spatial information (SI). The TI and SI were calculated as described in [48].

B. Generating flickering versions of the compressed test videos

To assess the QP at the JND in a sequence of compressed versions of a source video, observers compare compressed videos with the source video and report whether they perceive a difference between them. The two videos to be compared are presented in random order, and the observer must choose the distorted video. The videos in the comparison can be played side-by-side or sequentially. As an alternative to playing back the compressed video, we adapted the flicker test proposed by the ISO/IEC standard 29170-2 for image quality assessment [40] to image sequences as follows.

The frames of the source video alternate with the frames of a compressed version with a temporal frequency of 8 Hz. For example, suppose a source video has a frame rate of 24 fps. Then, the first three frames of the source video are played, followed by the next three frames, taken from the encoded version. Next, the subsequent three frames of the source video are played, and the process continues in this way. We decoded the source and compressed the videos into RGB frames to create the flickering videos. The observers are presented with these flickering videos side-by-side with the source video and asked on which side they notice any flicker.

The generated flicker videos have a resolution of 1920 $\times$ 1080 pixels, which is not practical for crowdsourcing. Therefore, we cropped the sources, the flickering, and the compressed videos to 640 $\times$ 480 pixels.

C. Video transmission to crowd workers

In our empirical study, we compared compressed and source videos, as well as flickering and source videos, side by side. For our online experiment, several such comparisons were grouped in batches to be processed by observers. To avoid stalling and other network and bandwidth-related issues, all videos that were scheduled in a batch were pre-loaded onto the participant's computer before playback. A flickering video generally has a high bitrate that is roughly the same as that of the source video because it contains frames from the source. Therefore, we encoded the videos for transmission in a visually lossless setting to reduce the download time in crowdsourcing.

In previous work involving videos in crowdsourcing, authors kept file sizes manageable by compressing the videos with a constant rate factor (CRF) of 18 in [49], by using an average file size of 1.23 MB in [50], or by cropping the high-resolution videos to 540p in [10]. In our work, we compressed the videos with a CRF of 12 to ensure perceptually lossless compression. We conducted a pilot study to compare the JND location assessed by a small group (10 people) for 10 source videos at CRFs of 5, 10, and 12 using the flickering test. We found that there was no statistically significant difference between the JND locations when these CRFs were used. Therefore, we set the CRF to 12 to encode the video sequences for transmission in our main crowdsourcing experiment.

For visually lossless compression of the videos, we used the x264 implementation of H.264/AVC with the "high" profile and "veryslow" preset. We used CRF rate control and a GOP size equal to the frame rate.

We used a commercial global content delivery network service for fast, low-latency delivery of the test videos. Prior to playback, the videos were pre-loaded onto the users' machines.

V. Crowdsourcing study for JND assessment

In our online experiment, we collected paired comparison responses to estimate SUR curves for all combinations of source videos, codecs, and test modalities. Thus, for each of the 45 source videos, we estimated the collective psychometric functions for the following sequences of stimuli:

- Compressed with AVC (QP $= 0, \ldots, 51$),
- Compressed with AVC (QP $= 0, \ldots, 51$) and interleaved with the source,
- Compressed with VVC (QP $= 0, \ldots, 63$),
- Compressed with VVC (QP $= 0, \ldots, 63$) and interleaved with the source.

This yielded 180 SUR curve estimations. We defined a *question* as showing a participant a side-by-side paired comparison. In the flicker test, the participants were asked to identify the side with the flickering video. In the plain test, the participants were asked to identify which side showed the lower quality video.

We used the freelancer.com platform (www.freelancer.com), an online job marketplace that allows *clients* and *freelancers* to collaborate. On this platform, *clients* create and submit projects and *freelancers* bid to conduct the work. *Freelancers* can communicate and chat with the *client*. *Clients* can also contact their *freelancers*.

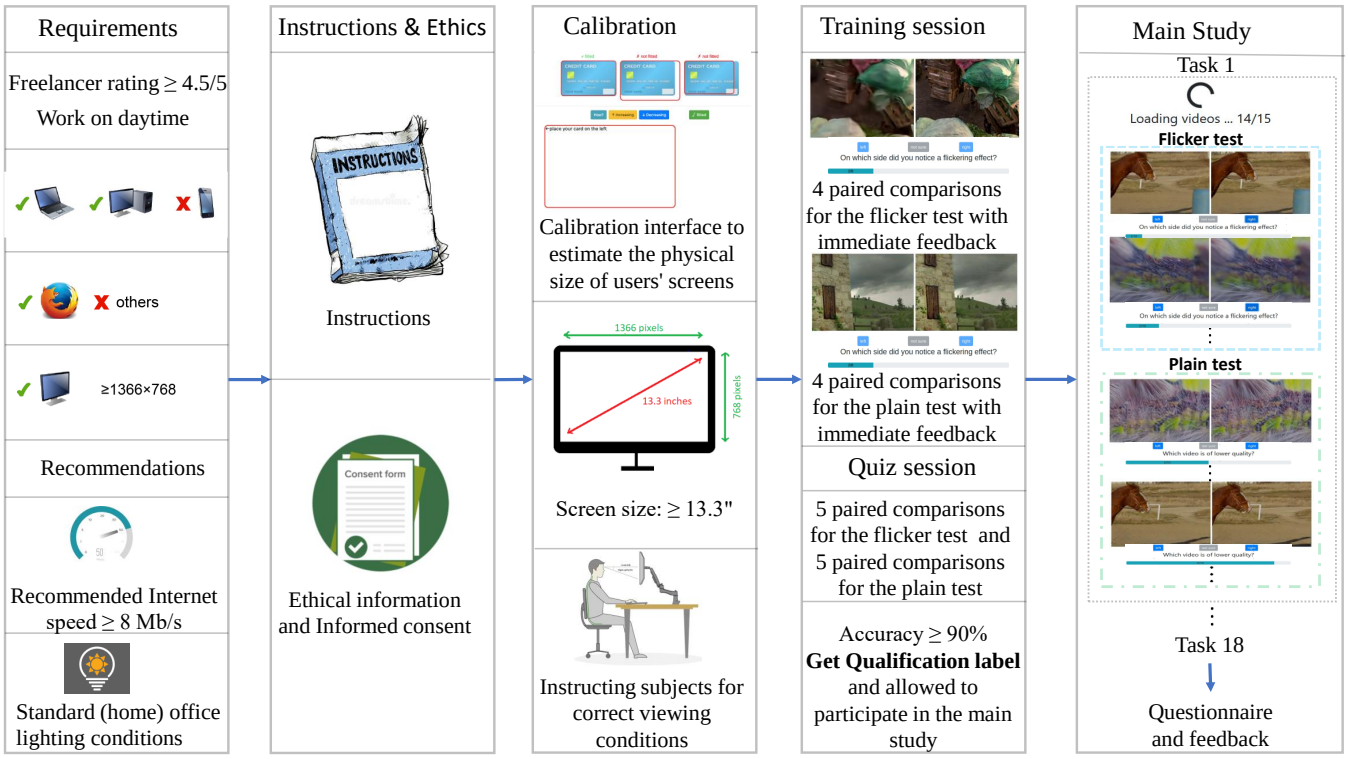


Fig. 6: Workflow of the online subjective JND-based video quality assessment study. The source code for the web interface is available at https://github.com/jenadeleh/JND-Video-Quality-Web-Interface.

A. Overview

Fig. 6 shows our experiment's procedure. To be eligible to participate in the main study, subjects were required to sign a consent form and obtain a qualification label by passing a quiz. The main study was divided into many small tasks. Once a task was completed, a subject could take a break before proceeding to the next task.

B. Requirements

To ensure quality, we invited freelancers with a rating of at least 4.5/5 from their previous jobs. The following requirements were automatically checked.

- Desktops and laptops were allowed, while cell phones and tablets were not allowed.
- Firefox browser.
- Minimum logical resolution of 1366×768 pixels.
- Work was allowed only during the day in the freelancer time zone.
- Minimum screen size of 13.3 inches.

We used the JavaScript "navigator" object to access the user agent information and determine the type of device being used by the participants. To obtain the logical resolution of the screen used by a browser, we used JavaScript and the "window" object's properties. Participants were instructed to maximize their browser window. If the browser was not maximized, participants were prompted to maximize the browser, and the experiment was paused until compliance was ensured. The method used to estimate the physical screen size of the users is described in Section V-E.

To display the entire graphical user interface (GUI) of our subjective experiment, participants were required to have a display with a minimum logical resolution of 1366×768 pixels and a minimum physical size of 13.3 inches. The pixel density for screens with this resolution and size is 117.8 pixels per inch (PPI). In this case, the stimuli were displayed with a one-by-one pixel ratio. Upsampling was conducted for screens with higher pixel densities, while downsampling was conducted for screens with lower pixel densities. Upsampling does not cause any information loss and can be expected to have only a negligible effect on perceived quality. The downsampling yielded only a slight reduction in the logical image pixel density from 117.8 PPI to 102.46 PPI in the worst case. Therefore, we do not expect that this process significantly affected the results of the paired comparisons.

Moreover, freelancers were advised to verify that their Internet download speed was at least 8 Mb/s.

C. Instructions

Participants were given instructions in four steps. In the first step, they were familiarized with the flickering videos and the flicker effect by showing a source video, followed by two flickering versions: one with barely perceptible distortion (flicker effect) and one with strong perceptible distortion.

In the second step, a paired comparison of a source video and a flickering version was shown for 5 s. This was followed by a 3 s phase in which an interface gave the subjects options for choosing the side of the flickering video or pressing the "not sure" button. The "not sure" option was used for paired

comparisons in [51] to reduce stress and fatigue. In [52], we demonstrated through a subjective study that the inclusion of the "not sure" response option in the forced-choice method reduces mental load and results in models with improved goodness of fit. In the third step, we familiarized the participants with the compressed videos. Another source video and two compressed versions were shown, one with barely noticeable distortion and one with heavy compression artifacts. In the fourth step, a paired comparison of a source video and its compressed version were shown for the plain test. Finally, the study and the payment methods were explained.

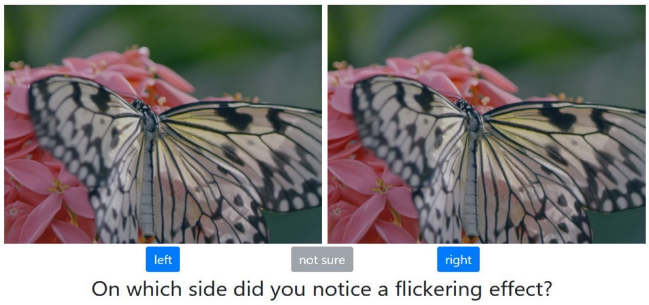


Fig. 7: User interface for the flicker test.

D. Ethics

Ethical approval for the experimental procedures and protocols was granted by the Institutional Review Board of the University of Konstanz. Participants were informed about the study's purposes and legal rights. The patients had the chance to ask questions and were requested to provide informed consent.

E. Calibration

In an online assessment of perceived video quality, ensuring uniform experimental conditions for all participants is challenging [53]. For example, stimuli will have different physical sizes on screens of different sizes and resolutions, which could affect the perceived video quality. Therefore, we displayed videos with a fixed physical size on all participants' screens and recommended a fixed viewing distance. For this purpose, we implemented the calibration method described in [14] to estimate the physical size of the screens of the participants. In this method, after the minimum resolution described in Section V-B is imposed, the screen size is estimated using the virtual chinrest method [54].

As a result, each video was rendered on all participants' screens with a fixed physical size of $138\,\mathrm{mm} \times 103.5\,\mathrm{mm}$. Therefore, for the side-by-side comparison, a fixed physical size of $281\,\mathrm{mm} \times 103.5\,\mathrm{mm}$ was used, including $5\,\mathrm{mm}$ of white space between the paired videos. The corresponding calibration parameters were stored in the local memory of the participants' browsers. If the browser zoom level was changed after calibration, the participant was asked to restore the zoom level or redo the calibration.

We also asked the participants to adjust their viewing distance to $60\,\mathrm{cm}$. This distance was derived by the trigonometric calculation described in [54] and the ISO standard [55] for two videos of width $138\,\mathrm{mm}$ with a $5\,\mathrm{mm}$ blank space between them.

F. Training session

To guide the participants in using our user interface and familiarize them with the subjective task, we asked them eight questions. The first four questions were presented using the flicker test. The participants were shown a flickering video with its high-quality source video and asked to choose "right", "left", or "not sure" in response to the question "On which side did you notice a flickering effect?" (Fig. 7). These stimuli were manually selected. The stimuli in two questions were compressed using AVC, and the stimuli in the other two questions were compressed using VVC. The next four questions were presented using the plain test. The test question was "Which video is of lower quality?"

The order of the questions was randomized at the beginning of each training session for each participant. Participants were not allowed to work on a question until the required videos for all the training questions were fully loaded. In one training question in both the flicker test and plain test, two identical videos were compared side by side. Only the answer "not sure" was correct for this question. In another training question, the source video was compared to a highly compressed video or a video with a strong flicker effect. The only correct answer was to choose the side of the compressed/flickering video. In two other questions, a source video was compared to its compressed or flicker version with barely perceptible distortion. Choosing the side of the compressed video or "not sure" was the correct answer for these questions. If the answer was correct, a message confirmed that the participant made the right choice. If the answer was incorrect, a message explained why the choice was incorrect and explained the correct answer to the participant.

For each question, the source stimulus and its flickering or compressed version were presented side by side randomly on the left and right sides. During playback, the "left" and "right" buttons were enabled, but the "not sure" button was disabled. If the participant made a choice before the end of the video (5 s), the next question was shown. Otherwise, the participant was shown a decision-making interface for $3\,\mathrm{s}$. In this interface, the "left", "right", and "not sure" buttons were enabled. A progress bar was presented to visualize the progress of the participant.

G. Quiz session

Participants were required to complete a quiz to participate in the main study. The quiz consisted of ten questions, with the first five concerning the flicker test and the remaining five concerning the plain test. Although the content of the quiz videos differed from that of the training videos, the steps for answering a quiz question were the same as those for answering a training question, except that no feedback was provided to participants after each quiz question.

In the quiz session, the compared videos were identical in one question for each test condition, i.e., the flicker test or plain test. For this question, the answer "not sure" was correct. In another question, the flicker effect or compression level was strong. The correct response was to select the side of the

flickering, or the compressed video. For the remaining three questions, the stimuli had barely perceptible distortions around the JND location assessed by the authors. Therefore, for these three questions, choosing the side with the flickering, resp. compressed video or pressing the "not sure" button was correct.

Once a participant completed the quiz, the result was sent to our server. Participants with a score of at least eight correct answers out of the ten questions received a qualification label, and a new page with the link to the main study was displayed. Participants with lower scores received a message informing them of their failure and were not allowed to repeat the training and quiz sessions.

H. Main study

When a participant with a valid qualification label opened the link to the main study, the requirements presented in Subsection V-B were checked. If these conditions were satisfied, the local browser storage was checked to determine whether the calibration was complete. If the calibration was complete, the participant was allowed to begin the main study. If the browser window was not already maximized, the participant was asked to maximize it. On the other hand, if no record was saved in the browser's local storage, the participant had to repeat the calibration, training, and quiz.

For each sequence of stimuli, the sequence of QPs that defined the requested paired comparisons was generated adaptively by QUEST+. After a participant completed the paired comparisons in a task, the results were sent to the corresponding QUEST+ objects in our server, and the next QPs were determined for delivery to other participants.

Each task consisted of ten questions presented in two parts. In the first part, five different sources were randomly picked together with one of the two encoders, the AVC or VVC, and the flicker test condition. In the second part, the same five source videos and encoders were used, but the plain test was included. The QPs for all compressed resp. flickering versions were determined by QUEST+.

This task structure enabled a within-subjects study design for comparing the flicker test to the plain test.

We used the collective observer method described in Section III to estimate each of the 180 collective psychometric functions. To emulate the collective observer, we restricted our subjects to providing only a single response to the paired comparisons per sequence of stimuli. Furthermore, because the paired comparisons were presented to participants in batches of 10, each participant could complete no more than 18 tasks containing 10 comparisons each.

To correctly assemble the tasks for delivery to participants, our server maintained a table of available paired comparisons and a list of comparisons already issued to each participant. The table showed whether there was a next available QP for each of the 180 combinations of the source video, encoder, and test conditions. If there was, that QP was given. Otherwise, a flag was set.

For each task, the server uploaded 15 videos to the computer of a freelancer: five source videos (used in both parts of the task as source videos), five compressed versions (for the plain test), and five compressed and interleaved versions (for the flicker test). After the download was completed, the participant could begin answering the corresponding 10 questions. As in the training session, video pairs were played for $5\,\mathrm{s}$. Participants who did not make a decision during these $5\,\mathrm{s}$ were given an additional $3\,\mathrm{s}$ to make their decision.

When the task was finished, the participant was given the option to rest, reread the instructions, perform the next task, or quit the experiment. Additionally, counters that showed the number of completed tasks and the remaining open tasks were shown.

If a participant failed to respond to a paired comparison in the flicker or plain test within $8\,\mathrm{s}$, the corresponding question for the same source video in the other test condition was discarded. Both questions were then reassessed in the following tasks.

VI. Experimental results

In total, 67 freelancers participated in the training session and took the quiz. Of the 57 freelancers who passed the quiz, 55 placed a bid. Then, through the freelancers.com chat tool, the first author discussed the project with them to ensure that they fully understood the test. Of the 55 freelancers who submitted a bid, 51 took part in the study. Some demographic and experimental data collected through questionnaires from the freelancers are illustrated in Fig. 8.

The average time taken by freelancers to complete the initial tasks, including reading instructions, completing the consent form, and performing calibration, was 5:21 min. The training session lasted approximately 1:45 min, and quiz session lasted an average of 1:09 min.

Workers who passed the quiz were eligible to participate in the main study, where they completed up to 18 assignments. Each assignment consisted of 10 paired comparisons (5 for each test condition). On average, workers spent 0:57 min answering the 10 questions in each assignment. The duration of video preloading was not considered in these calculations.

A. Data filtering

In the subjective experiment, we used the relaxed forced-choice method. This method provides the "not sure" option in addition to the "right" and "left" stimuli. With the flicker test, a reliable subject would either correctly select the flickering video or press "not sure" if the flicker effect was below the perceptual threshold. Therefore, a subject who selected the source video was considered inattentive at this time, and we discarded these responses and their corresponding responses for the plain test to ensure a within-subjects design. For the plain test, we proceeded accordingly. As a result, we removed 5.24% of all the responses. We then reconstructed the psychometric functions of the population based on the remaining responses.

B. Probability distribution fitting

To construct the psychometric function in (6), we used the Weibull cumulative distribution function

$$F(x;\alpha,\beta) = 1 - e^{-(x/\alpha)^{\beta}} \quad \text{for} \quad x \geq 0 \tag{7}$$

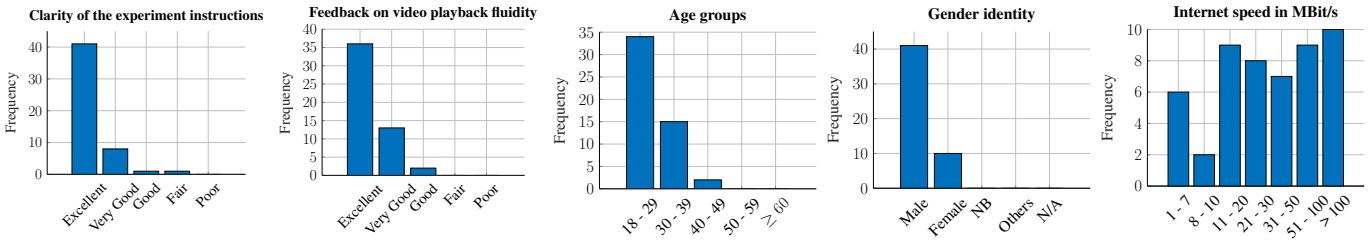


Fig. 8: Participant diversity and experimental insights: Data from 51 freelancers in the subjective study.

where $\alpha > 0$ is the scale parameter and $\beta > 0$ is the slope. The Weibull distribution is flexible and allows the fitting of nonsymmetric curves.

The fitting is based on the maximum likelihood estimation. Since each psychometric function can specify only the probability of correct detection, we also needed to define the probability of the "not sure" response. In the model with the 2AFC setting, the participant does not have the "not sure" option and would have to randomly select one of the sides "left" or "right". This led us to treat the "not sure" response as two responses, one for "left" and one for "right", each weighted by a factor of 1/2.

Using QUEST+, we incorporated the lapse rate parameter λ of the psychometric function (6) into the estimation along with the scale α and the slope β. Between 43 and 51 paired comparisons were collected to estimate the parameters of a psychometric function. Fig. 9 depicts examples of the resulting SUR functions $\mathrm{SUR}(x;\alpha,\beta) = 1 - F(x;\alpha,\beta)$ for some source videos using the flicker test and the plain test.

To further compare the sensitivity and precision of the flicker test with those of the plain test, we calculated the JND threshold x_{JND} for each Weibull JND distribution with $F(x_{\mathrm{JND}};\alpha,\beta) = 0.5$ and variance $\sigma^2 = \alpha^2\left[\Gamma(1+2/\beta) - (\Gamma(1+1/\beta))^2\right]$, where Γ is the gamma function.

C. Sensitivity

Fig. 9 shows the estimated SUR curves for the flicker test and the plain test. Curves that are farther to the left indicate a more sensitive JND assessment because differences in the source video were detected for smaller QPs. This shift in the JND caused by the flicker test can be quantified by Δ_{JND}, the JND threshold assessed with the flicker test minus the threshold assessed with the plain test for the same source video compressed with the same video codec. The figure shows that the flicker test provided a more sensitive JND assessment ($\Delta_{\mathrm{JND}} < 0$) for the source videos SRC129, SRC193, and SRC009 and both the AVC and VVC codecs. However, for the source video SRC059, the plain test was more sensitive ($\Delta_{\mathrm{JND}} > 0$).

To summarize the comparison of the two test conditions for all 45 sources and both codecs, we show the boxplots of the JND thresholds for the videos compressed with AVC and VVC in Fig. 10 (a) and (c). The mean thresholds derived with the flicker test are smaller than those derived from the plain test (33.5 and 36.4 for the flicker test vs. 34.1 and 38.5 for the plain test). Parts (b) and (d) of the figure show the differences between the JND thresholds estimated with the flicker test and those estimated with the plain test. The differences are negative in most cases. Overall, the results indicate that, on average, the flicker test was more sensitive than the plain test.

To check whether this finding was statistically significant, we conducted a nonparametric paired-samples Wilcoxon signed-rank test to test the hypothesis that the flicker test has a higher sensitivity than the plain test.

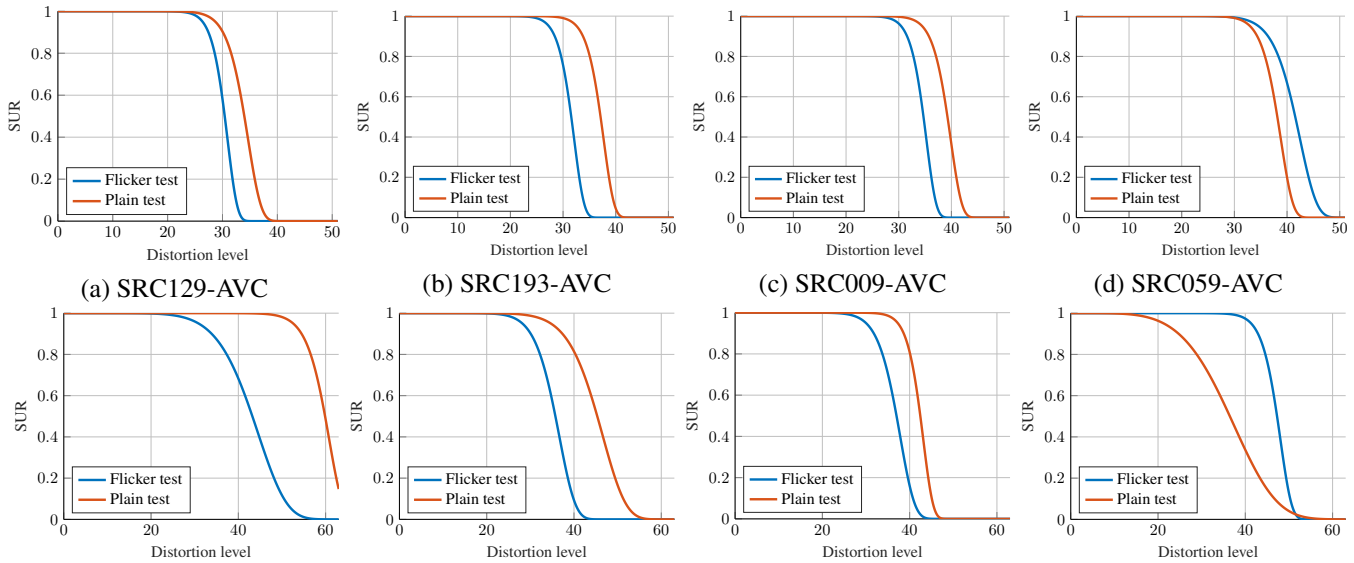
The null hypothesis was that the median of the JND differences for the same source videos and compression codec comes from a distribution with a median of zero, and the alternate hypothesis was that the median is less than zero. The p-value for the test was 0.0004, which indicates that the null hypothesis was rejected at the 95% confidence level, supporting the greater sensitivity of the flicker test.

However, the flicker test was less sensitive than the plain test ($\Delta_{\mathrm{JND}} > 0$) for 16 of 45 source videos for AVC compressed videos and for 10 of 45 source videos for VVC compressed videos, as shown in Figs. 9 (d, h) and 10 (b, d). This may be due to the strong motion in the videos, which may have masked the flicker effect. Videos with strong motion have large temporal information. Fig. 11 shows the temporal information versus Δ_{JND}. The plain test is more sensitive when $\Delta_{\mathrm{JND}} > 0$, i.e., in the region on the right side of the vertical line. The source video sequences, determined to have high motion through a visual inspection conducted by the authors, were marked with crosses. For most of these videos, the flicker test did not yield higher sensitivity. This confirms that strong motion in the video may indeed mask the flicker effect, thereby reducing the sensitivity.

D. Precision

As is common in statistics, we express the precision of a random variable as the reciprocal of its variance. A small variance of the collective JND indicates high precision and typically corresponds to a larger (absolute) slope of the SUR curve at the JND threshold, as seen in the examples for the flicker test in Fig. 9. To compare the two test conditions for all 45 sources and both video codecs, we draw boxplots of the variances of the JND distributions and the pairwise differences of variance in Fig. 12. The variances derived from the flicker test are typically smaller than those from the plain test. A negative $\Delta_{\mathrm{Variance}}$ was observed in 35 of the 45 source videos for AVC compression and in 26 of the 45 source videos for VVC compression.

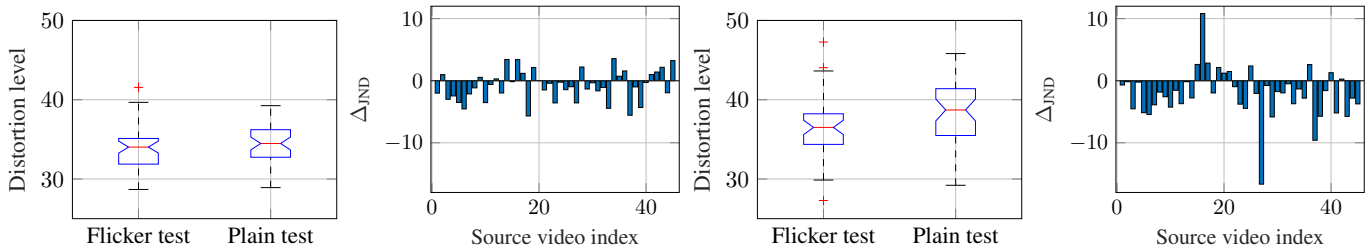
We applied the paired-samples Wilcoxon signed-rank test to test the hypothesis that the flicker test yields smaller variances in the estimated JND distributions and thus provides greater precision in JND threshold assessment than the plain test. The null hypothesis of the test was that the differences between the



(a) SRC129-AVC (b) SRC193-AVC (c) SRC009-AVC (d) SRC059-AVC

(e) SRC129-VVC (f) SRC193-VVC (g) SRC009-VVC (h) SRC059-VVC

Fig. 9: SUR curves for the flicker test and the plain test. The first three columns show the SUR curves with and without the flicker test for the source videos with the smallest (negative) Δ_{JND} values, averaged for AVC and VVC, while the fourth column shows them for the source video with the largest average Δ_{JND}.



(a) AVC (b) AVC (c) VVC (d) VVC

Fig. 10: Comparison between the JND thresholds estimated via the flicker test and the plain test. The boxplots in (a) and (c) summarize the statistics of the JND thresholds for the flicker test and the plain test, respectively. The bars in (b) and (d) show, for each of the 45 source videos, the difference Δ_{JND} between the JND threshold estimated with the flicker test and that estimated with the plain test. A negative difference indicates that the flicker test is more sensitive.

variances for the same source videos and compression codecs come from a distribution of zero median, and the alternate hypothesis was that the median is less than zero. The p-value of the test was 0.033, clearly rejecting the null hypothesis at the 5% significance level.

E. Time complexity

The flicker test required more time than the plain test during the experiment. The flickering videos have approximately the same bitrate as the source video. For the plain test, compressed videos are transmitted, which requires much less download time (Sec. IV-C). However, the waiting time for the complete upload of all the videos required for a task with flicker tests was less than twice as large as that for plain tests.

The response time is the duration from the start of the display of the stimuli to the time when the participant pressed one of the "left", "right", or "not sure" buttons. In our experiment, the response time for paired comparisons with the flicker test was slightly longer than that for the plain test: 5.0 s for the flicker test vs. 4.7 s for the plain test. However, this difference is very small and hardly relevant for subjective experiments.

Fig. 13 compares the cumulative distribution of the participants' response times for the flicker and plain tests. For more than half of the comparisons, the response time was greater than 5 s, which is the duration of the videos. In these cases, participants viewed entire paired videos before making their decision within the 3 s window following the video playback.

The cumulative response time curves for both tests sharply increase in steepness approximately 500 ms after the end of the video playback. This corresponds well to the expected reaction time required for a participant to press one of the buttons when the video playback is finished.

VII. Conclusion

When compressing video sequences to smaller bitrates, the probability that an observer will not see any distortion in the reconstructed video is of interest in many applications. In this paper, improvements of methods for estimating these so-called

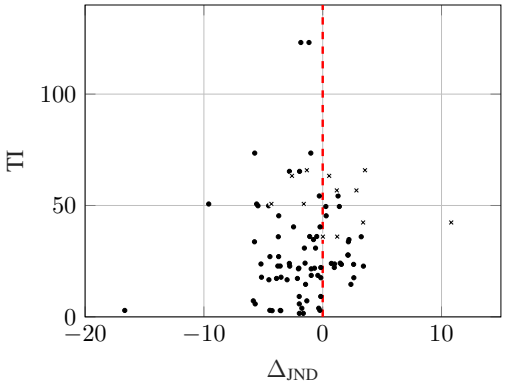
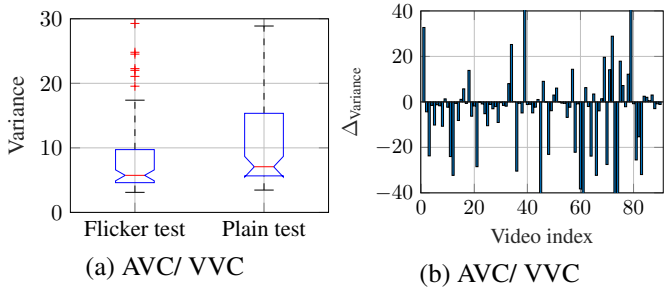


Fig. 11: Temporal information (TI) vs. Δ_{JND} for 45 source videos encoded with AVC and VVC. The videos marked with crosses (x) exhibit high motion, as determined by visual inspection conducted by the authors. The remaining source videos are represented by filled-in circles (•).



(a) AVC/ VVC (b) AVC/ VVC

Fig. 12: Comparison between the variances of the JND distributions estimated with the flicker test and the plain test. The boxplots in (a) show the summary statistics. The bars in (b) show the difference between the variances estimated with the flicker test and the plain test. Video indices 1 to 45 denote the AVC compressed sources, and 46 to 90 denote the VVC compressed sources. A negative difference indicates that the flicker test was more precise.

satisfied user ratios are presented. We showed that the common procedure of fitting a distribution model to JND thresholds suffers from bias. This bias is avoided using our proposed collective observer method, in which a randomly selected observer responds to each comparison of a compressed video with its source. This approach is more efficient than estimating and averaging the psychometric functions of many individual observers. To estimate the collective psychometric function, we applied an adaptive psychometric Bayes method, QUEST+, in a crowdsourced environment.

For our experimental work, we adapted the flicker test for paired video comparisons. This test was originally developed for evaluating near-lossless image coding. Using a within-subject study design, we implemented a web-based user interface for evaluating video quality under two test conditions, i.e., the flicker test and the plain side-by-side comparison. This web interface and the crowdsourcing environment were managed by our server application. The application ran multiple parallel instances of QUEST+ to adaptively determine

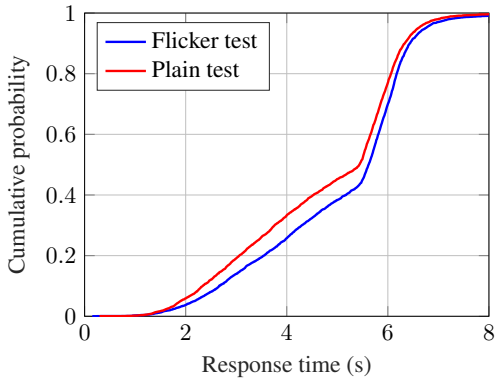


Fig. 13: Cumulative response time for paired comparisons.

the stimuli delivered in each task for each study participant. We estimated the SUR curves of 45 source video sequences encoded with AVC and VVC at all available QP values. The results showed that the flicker test yielded a more sensitive and precise JND-based video quality assessment than plain side-by-side presentation. Our dataset will be made available online at the time of publication.

Our approach provides a foundation for larger and better quality datasets of JNDs in video compression and corresponding SUR curves. In our future work, we will conduct a large-scale crowdsourcing campaign. Furthermore, in a laboratory study, we will evaluate the JND and SUR curves for high-resolution videos of 1920×1080 and 3840×2160 pixels.

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