Abstract—Human perception is at the core of lossy video compression and yet, it is challenging to collect data that is sufficiently dense to drive compression. In perceptual quality assessment, human feedback is typically collected as a single scalar quality score indicating preference of one distorted video over another. In reality, some videos may be better in some parts but not in others. We propose an approach for collecting finer-grained user feedback through an interactive tool that allows direct optimization of perceptual quality given a fixed bitrate. To this end, we built a novel web-tool which allows users to paint spatio-temporal importance maps over videos. The tool allows for interactive successive refinement: we iteratively re-encode the original video according to the painted importance maps, while maintaining the same bitrate, thus allowing the user to visually see the trade-off of assigning higher importance to one spatio-temporal part of the video at the cost of others. We use this tool to collect data in-the-wild (10 videos, 17 users) and utilize the obtained importance maps in the context of x264 coding to demonstrate that the tool can indeed be used to generate videos which, at the same bitrate, look perceptually better through a subjective study ($n=20$) — and are 1.9 times more likely to be preferred by viewers. We plan on collecting a large-scale dataset using the tool for automated perceptual compression in the future. The code for the tool and dataset can be found at https://github.com/jenyap/video-annotation-tool.git

Index Terms—video compression, perceptual compression, visual importance, tool, dataset

I. INTRODUCTION

More than 80% of the internet comprises of videos, and this fraction is growing by the day [1]. The landscape of video has been evolving quickly over the last few years, spanning a multitude of use-cases such as VOD streaming, social networking, live communication, and remote learning. While the applications are diverse, many feature an important common denominator: the videos are ultimately consumed by humans. This has motivated decades of work on perceptual quality assessment, perceptual quality metrics, and perceptual compression (see [1], [2] for reviews). However, in order to generate videos better suited for human consumption, a key question remains: what is the best way to collect data in order to perform better perceptual video compression? The fields of image and video quality assessment have refined the art and science of collecting subjective data via human feedback. However, the output is usually only a scalar value per video (ACR) or comparison of videos (DCR) [3], [4]. While this certainly provides useful information, it doesn’t provide information that is sufficiently specific to drive a video compression algorithm. In order to get spatio-temporally dense importance maps, a related field of work utilizes pre-existing saliency regressors driven by human attention to predict the importance maps which can be used for region-of-interest compression [5]–[7]. However, this approach only indirectly gets at the core issue because compression artifacts can grasp our attention and modify the perceived saliency [8].

We introduce a novel approach where people use an interactive tool to directly optimize the perceptual quality of a video given a fixed bitrate. The tool allows for collecting finer-grained feedback in the form of spatio-temporal importance maps. We demonstrate using a subjective survey that videos compressed with the human-specified importance maps are 1.9 times more likely to be preferred over videos of the same size compressed in the traditional way. We believe this result is just the beginning of this line of research. The data collected through this tool directly tells us which spatio-temporal regions impact the perceptual quality of a video as determined by humans. The importance maps can be used to design new perceptual quality metrics, as well as new compression algorithms based on predicting importance maps.

II. RELATED WORK

Perceptual Quality (PQ) is inherently subjective and as such requires human feedback. The objective of incorporating PQ into the design of video compression and evaluation metrics is a long-standing one, and as such has given rise to a considerable body of literature built over the span of more than two decades. However, to our knowledge, none of the existing works directly tackle the question of: which spatio-temporal regions do viewers find important in compressed videos? Below we delineate the various related works, which we compare and contrast to ours.

A. Scalar Quality Score Collection

Several procedures have been developed by the International Telecommunication Union (ITU) to assess the quality of images and videos [3], [4]. The procedures can be roughly split...
into two main categories: *rating* in absolute terms, or *ranking* in relative terms. In rating, the observer is presented with a video and their task is to rate it with a score. For example, in ACR (Absolute Category Rating) the observer rates a video on a scale from 1 to 5 to reflect visual quality. In ranking, the observer is presented with two or more videos, and they are asked to rank the videos in order of preference. In both of these methods, the output score is only a single scalar, and as such cannot provide transparency into the critical question as to why each user provided this response. For instance, was it due to noticeable distortions to specific areas of interest? In our work, we focus on collecting spatio-temporal feedback on what an individual finds important in the video.

B. Saliency Map Collection

Predicting visual attention has been a field with longstanding interest, due to its widespread applications to many fields such as image/video quality assessment [9], [10], image/video compression [11], [12], and so on. In the past three decades, numerous works explored this question from different directions (see [5]–[7] for reviews). As humans can find different regions visually salient in a scene given the context, these approaches can be classified as either bottom-up [13]–[17] or top-down [18]–[21]. In top-down saliency detection, human visual saliency is detected under a given high-level task, whereas bottom-up saliency detection is stimulus-driven with the goal of identifying important visual features under more natural settings. In our work, we take a top-down approach, since lossy video compression introduces characteristic but undesirable artifacts, such as blocking, ringing and aliasing, and these artifacts can potentially shift the observer’s attention from the original regions of interest during iterative painting.

On the other hand, based on how the saliency maps are collected, the majority of the saliency literature focuses on either fixation prediction [22]–[25] or salient object detection [14], [18], [26], [27]. In fixation experiments, saliency is measured by tracking human gaze whereas in salient object detection, the goal is to find pixel-accurate segment maps of important objects in a scene. Unfortunately, gaze tracking is inherently non-scalable as it requires special equipment in a laboratory setting and most of the salient object detection focus on detection of one or few salient objects instead of the whole scene. In our approach, we allow unconstrained painting within the entire spatio-temporal volume by the user, enabling us to collect a fine-grained data at pixel level while being uninhibited by the limited segmented regions in the video.

Finally, many approaches have tried to exploit one of the many saliency models (or built their own) for the specific task of video compression [12], [28]–[31]. However, none of these methods directly collect the human spatio-temporal saliency maps explicitly for the task of video compression. In our work, we collect perceptual data from distorted videos in an interactive successive refinement process where the user provides immediate feedback on how the chosen saliency region impacts the encoded video — which, importantly, maintains any resultant compression artifacts within consideration.

III. INTERACTIVE SPATIO-TEMPORAL ANNOTATION TOOL

The annotation tool allows a user to iteratively refine a spatio-temporal importance map in order to improve the perceptual quality of an H.264-encoded video given a fixed bitrate budget. Below we present the workflow of the tool, the considerations in its design, and the implementation details.

A. Annotation Tool Workflow

Fig. 1 shows the workflow of the annotation tool. The user is presented with the H.264-encoded video on the left, and an annotation map on the right (referred to as annotation map frames). Annotation map frames act as a canvas for the user to mark particular areas where they want higher quality (i.e., lower distortion). The annotation tool allows the user to paint
Importance map

x264 default

x264 with the importance map

Fig. 2: Example of user-annotated importance map frames, frames from video encoded with the default x264 implementation, and frames from video encoded with x264 using the importance maps. In this case, it can be seen that the reconstructions are sharper and have higher quality in the areas that were assigned with high importance. See Sections III-B and III-D for more detail.

areas of importance in the annotation map frames iteratively. Each iteration can be broken down into 4 steps:

S1: In the first step, the user paints areas of the annotation map frames where they want to see better quality (or conversely erase areas where higher quality is not needed). We refer to the result of the user’s marking as an importance map (Section III-B).

S2: The user-generated importance map is sent over to the back-end server, to regenerate the encoded video based on the importance map.

S3: The backend-server regenerates the encoded video based on the received importance map using the x264 video encoder, at a fixed bitrate (Section III-D).

S4: When the encoding is finished, the encoded video is sent back to the browser. On the left, the user is presented with the newly re-encoded video, and on the right with the updated importance map (which is temporally propagated to facilitate future frame annotation; see Section III-C). This provides the user with immediate feedback and allows for iterative refinement of the importance map.

The user repeats steps S1-S4 until they are content with the result. Once the user presses on the ‘Next Video’ button (Fig. 1b), the final importance map is saved on the back-end and a new video is presented.

B. Importance Map Specification and Annotation

The user can refine the importance map for each frame. Importance map values for each frame are in the range of 0 to 255 represented as a red mono-color frame in the tool. The user marks an area as important, its value increases and it is reflected in the front-end as a redder-region. To start, all pixels of the annotation map are initialized to 127. We also overlay source video edges on the annotation map to assist with the painting.

The user can either increase the importance of an area by using the brush, or decrease it by using the eraser (Fig. 1b). The brush size can be adjusted, allowing the user to mark large areas quickly, or conversely to focus on finer-grained details. Both the coloring and erasing operations are implemented using additive functions, which spatially decay with the brush radius. In order to dissuade the user from coloring the entire video in red (255), the importance map is normalized to an average pixel value of 127 and the normalized importance map is presented on the right.

C. Temporal Propagation of the Annotation Map

To facilitate the annotation, each time the user paints on the canvas, we propagate their marking to the future frames. If a user marks a certain area/object as important, we expect it to remain important for the next few frames. To that end, we estimate the optical flow between consecutive frames, and utilize this estimate to propagate the paintings between frames. An example of such propagation is shown in Fig. 3.

As the optical flow estimation algorithms are not perfect and neither is the user-generated mask, this can sometimes lead to errors in the annotation map propagation. Note, however, that the user can manually correct the annotation map in such a scenario. To mitigate the errors in the optical flow estimation, the annotation map is only propagated to the next 40 of frames, and is decayed linearly temporally. For efficiency, the optical flow is pre-computed and stored on the back-end server. We used the off-the-shelf OpenCV implementation of the Farneback algorithm to estimate the optical flow.

D. Encoding Parameters: Modifications to the x264 Encoder

In order to optimize perceptual quality given a fixed budget, videos are compressed into H.264-compliant bitstreams using x264 (the most commonly used H.264 encoder) using the importance map.

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The videos were chosen from the Video Compression Challenge Video Dataset. The subjective study can be found in our GitHub repository.

In our evaluations, we used 10 videos, each of 3-5 seconds. The videos were chosen from the Video Compression Challenge in CLIC 2021. See Section IV-C for more detail.

To collect the annotation data, we installed our annotation tool on a Google Cloud Platform (GCP) VM. We used Amazon Mechanical Turk (MTurk) to collect the importance map data. MTurk workers were required to have the “masters” qualification and lifetime approval rate greater than 98% to be qualified for our study. Each annotator was asked to annotate 5 random videos from the dataset, and was requested to spend at least 3 minutes on each video. This was enforced by disabling the “Next video” button for 3 minutes. The annotation tool provides a unique ID for each user that uses the tool. Using this ID we aggregated all the saved importance map by user. We also collected, for each user, intermediate importance maps (maps recorded while the user was using the tool) and x264 encoding statistics. We disqualified data collected from users who did not complete annotation task — for example, users who just waited for the ‘Next video’ button to become enabled before completing the annotation task.

We validated that the tool functions as desired via a subjective study of the collected importance maps. For each video, we obtained the importance map from the categories ‘Animation’, ‘Games’, ‘Lecture’, ‘Live Music’, ‘Sports’ and ‘Vlog’. Each video was resized to match our annotation tool’s video dimensions (800 × 450) and cropped to be less than 5 seconds. All of the video clips belong to a single scene. To account for content variability, all the videos were encoded at a bitrate such that the resulting output has a PSNR (RGB) of 25, resulting in encoded videos with a bitrate range of 50-750 kbps.

B. Importance Map Collection

To collect the annotation data, we installed our annotation tool on a Google Cloud Platform (GCP) VM. We used Amazon Mechanical Turk (MTurk) to collect the importance map data. MTurk workers were required to have the “masters” qualification and lifetime approval rate greater than 98% to be qualified for our study. Each annotator was asked to annotate 5 random videos from the dataset, and was requested to spend at least 3 minutes on each video. This was enforced by disabling the “Next video” button for 3 minutes. The annotation tool provides a unique ID for each user that uses the tool. Using this ID we aggregated all the saved importance map by user. We also collected, for each user, intermediate importance maps (maps recorded while the user was using the tool) and x264 encoding statistics. We disqualified data collected from users who did not complete annotation task — for example, users who just waited for the ‘Next video’ button to become enabled or annotated only a small part in just one frame.

Figure 2 shows example importance maps collected using the tool. It can be seen in the obtained frames that the tool indeed produces higher quality encodes in the regions identified as important by the annotator.

C. Validation via a Subjective Study

We validated that the tool functions as desired via a subjective study of the collected importance maps. For each video, we obtained the importance map from the categories ‘Animation’, ‘Games’, ‘Lecture’, ‘Live Music’, ‘Sports’ and ‘Vlog’. Each video was resized to match our annotation tool’s video dimensions (800 × 450) and cropped to be less than 5 seconds. All of the video clips belong to a single scene. To account for content variability, all the videos were encoded at a bitrate such that the resulting output has a PSNR (RGB) of 25, resulting in encoded videos with a bitrate range of 50-750 kbps.

IV. EXPERIMENTS AND RESULTS

The dataset, obtained importance map and videos used for the subjective study can be found in our GitHub repository.

A. Video Dataset

In our evaluations, we used 10 videos, each of 3-5 seconds. The videos were chosen from the Video Compression Challenge in CLIC 2021. See Section IV-C for more detail.

To collect the annotation data, we installed our annotation tool on a Google Cloud Platform (GCP) VM. We used Amazon Mechanical Turk (MTurk) to collect the importance map data. MTurk workers were required to have the “masters” qualification and lifetime approval rate greater than 98% to be qualified for our study. Each annotator was asked to annotate 5 random videos from the dataset, and was requested to spend at least 3 minutes on each video. This was enforced by disabling the “Next video” button for 3 minutes. The annotation tool provides a unique ID for each user that uses the tool. Using this ID we aggregated all the saved importance map by user. We also collected, for each user, intermediate importance maps (maps recorded while the user was using the tool) and x264 encoding statistics. We disqualified data collected from users who did not complete annotation task — for example, users who just waited for the ‘Next video’ button to become enabled or annotated only a small part in just one frame.

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we compute an average importance map across annotators. The average importance map is used to create a final video, which is then compared against the baseline encoded video without any spatio-temporal importance at similar bitrate. The encoded baseline and importance-map-generated videos are compared for all examples in the dataset in a separate subjective study involving different subjects using a two-alternative forced choice (2AFC) approach. Both the encoded videos are presented side-by-side and subjects were asked to choose the preferred video. The subjective study was generated using the Qualtrics Platform and conducted using Amazon MTurk, with similar requirements on workers as described in Section IV-B. We also included sanity checks in our comparison: 3 pairs of videos were added to the study such that one amongst the pair was obviously better. Subjects who incorrectly selected even one of these videos with worse quality were rejected from the data analysis. This resulted in n = 26 subjects whose selections were incorporated in the reported results.

Figure 4 shows the results for the different input videos. The bar chart shows the fraction of viewers who preferred importance map encoded videos over the baseline videos for different contents. The error bars represent the 95% Confidence Interval using standard normal distribution assuming each choice can be modeled using a binomial distribution. On average, across the dataset, videos generated using the importance maps were 1.9 times more likely to be chosen over the baseline encoded videos. The importance map-based method outperforms the baseline on 7 out of 10 videos, performs at chance on 1 video, and underperforms on 2 videos.

To understand these failure cases of the tool, we dug deeper into the two videos (`Animation_1080P-0cdf`, `Gaming_720P-5ba2`) where baseline encodes were preferred over the importance map encodes. For the case of `Animation` video, we found that there were two salient objects in the video and different annotators preferred different objects during the importance map collection step, resulting in an average map which was largely agnostic to both the salient maps (Figure 5). This resulted in a video where neither of the salient objects were preferred but had added distortions and highlights the issue that the average importance maps might lead to a competition between the preferences of different annotators. On the other hand, for the `Gaming` video, we found that the annotators all agreed to focus on the central character which is moving around in an artificial background. However, due to the over-focus on the central character, the video ends up looking unnatural due to the sudden reduction in the quality of the background in the neighborhood surrounding the character. The large motion exacerbates this issue, making it feel like the high quality character is moving in a low quality background. This example highlights the issue that during the annotation task, an annotator might have higher focus on the particular region they are painting and not take into account the increased distortions in unmarked areas, as there is no reference video for them to compare their final encode against.

V. DISCUSSION AND FUTURE WORK

In this work, we proposed a tool which allows collecting importance maps directly for the task of perceptual video coding. Furthermore, we demonstrated that re-encoding using these annotations can produce videos that are preferred relative to the counterpart baseline encoding. This initial success suggests a wide variety of follow-up work that improves the data collection procedure and utilizes the obtained data.

First, the task can be made easier to understand and more can be done to automatically validate the data. For instance, users tend to begin by annotating the main objects in the scene without attending to emergent artifacts in the background. In one such failure case, users annotated a character in the foreground, resulting in significant artifacts in the background. The annotated video received lower scores when directly compared with the original. While we instructed annotators to look carefully at the background after their first pass of annotating, more validation is likely necessary. In terms of validating the data quality, we had to manually exclude users who, for instance, annotated only the first frame or did not perform any annotations at all. One approach would be to present the user their video side by side with the baseline and verify that they choose the video that they annotated.

Second, it would be informative to decompose the importance maps into various sources of viewer attention — originating due to the saliency of source content versus artifact-dependent attention. Independent of the underlying compression algorithm, some aspects of the source video catch the attention of the average viewer more or less readily. These may include increased attention on people/text or reduced sensitivity to fast-moving objects. However, compression-dependent artifacts also catch the eyes of the viewers. It would be important to understand the extent to which an importance map collected at one target bitrate is useful for encoding a video at another target bitrate. It is likely that importance based on compression artifacts would change with bitrates, but importance based on the source content would remain consistent. In our initial experimentation, we found that applying the importance maps to encoding at 1.5× the collected bitrate...
resulted in videos which were preferred 1.4 times compared to 1.9 times with original bitrates. Another important factor of variation is the extent to which the users annotate the videos differently. Some users may attend to different objects and others may be more sensitive to compression artifacts.

Third, it is highly likely that the importance maps can be predicted to a sufficient degree to enable automatic perceptual compression. With a neural network trained on a large dataset of compressed video-importance map pairs, the entire perceptual coding process could be automated. Finally, we believe that the collected importance maps can be useful for the creation of perceptual metrics. Much like [8], spatial localization of artifacts can be useful for measuring perceptual quality. One way to create a perceptual metric using our data would be to have an importance-map weighted distortion loss.

We plan on collecting a large-scale dataset using the tool for automated perceptual compression in future.

Perceptually-driven video compression is a well-known and important problem. This paper explored a novel approach to this problem by asking users to directly optimize the perceptual quality using an interactive tool. The crowd-sourced importance maps are leveraged to re-encode the videos and a 2AFC study confirms that users prefer these perceptually-coded videos. This paper lays the foundation for a wide variety of follow up work in the fields of perceptual video coding and perceptual quality assessment.

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