

## Article

# Summarization of Videos with the Signature Transform

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**Abstract:** This manuscript presents a new benchmark for assessing the quality of visual summaries without the need for human annotators. It is based on the Signature Transform, specifically focusing on the RMSE and the MAE Signature and Log-Signature metrics, and builds upon the assumption that uniform random sampling can offer accurate summarization capabilities. We provide a new dataset comprising videos from Youtube and their corresponding automatic audio transcriptions. Firstly, we introduce a preliminary baseline for automatic video summarization, which has at its core a Vision Transformer, an image–text model pre-trained with Contrastive Language–Image Pre-training (CLIP), as well as a module of object detection. Following that, we propose an accurate technique grounded in the harmonic components captured by the Signature Transform, which delivers compelling accuracy. The analytical measures are extensively evaluated, and we conclude that they strongly correlate with the notion of a good summary.

**Keywords:** video summarization; large language models; visual language models; CLIP; signature transform



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## 1. Introduction and Problem Statement

Video data have become ubiquitous, from content creation to the animation industry. The ability to summarize the information present in large quantities of data is a central problem in many applications, particularly when there is a need to reduce the amount of information transmitted and to swiftly assimilate visual contents. Video summarization [1–7] has been extensively studied in Computer Vision, using both handcrafted methods [8] and learning techniques [9,10]. These approaches traditionally use feature extraction on keyframes to formulate an adequate summary.

Recent advances in Deep Neural Networks (DNN) [11–13] have spurred progress across various scientific fields [14–21]. In the realm of video summarization, two prominent approaches have emerged: LSTM- and RNN-based models [22–24]. These models have demonstrated considerable success in developing effective systems for video summarization. Additionally, numerous other learning techniques have been employed to address this challenge [25–28].

In this study, we introduce a novel concatenation of models for video summarization, capitalizing on advancements in Visual Language Models (VLM) [29,30]. Our approach combines zero-shot text-conditioned object detection with automatic text video annotations, resulting in an initial summarization method that captures the most critical information within the visual sequence.

Metrics to assess the performance of such techniques have usually relied on a human in the loop, using services such as Amazon Mechanical Turk (AMT) to provide annotated

summaries for comparison. There have been attempts to introduce quantitative measures to address this problem, the most common being the F1-score, but these measures need human annotators and have shown that many state-of-the-art methodologies perform worse than mere uniform random sampling [31].

However, in this work, we go beyond the current state of the art and introduce a set of metrics based on the Signature Transform [32,33], a rough equivalent to the Fourier Transform that takes order and area into account and that contrasts the spectrum of the original video with the spectrum of the generated summary to provide a measurable score. We then propose an accurate state-of-the-art baseline based on the Signature Transform to accomplish the task. Thorough evaluations are provided, where we can see that the methodologies provide accurate video summaries, and that the technique based on the Signature Transform achieves summarization capabilities superior to the state of the art. Indeed, the temporal content present in a video timeline makes the Signature Transform an ideal candidate to assess the quality of generated summaries where a video stream is treated as a path.

Section 2 gives a primer on the Signature Transform to bring forth in Section 2.1 a set of metrics to assess the quality of visual summaries by considering the harmonic components of the signal. The metrics are then used to put forward an accurate baseline for video summarization in Section 2.2. In the following section, we introduce the concept of Foundation Models, which serves to propose a preliminary technique for the summarization of videos. Thorough experiments are conducted in Section 4, with emphasis on the newly introduced dataset and the set of measures. Section 4.1 gives an assessment of the metrics in comparison to human annotators, whereas Section 4.2 evaluates the performance of the baselines based on the Signature Transform against another technique. Finally, Section 5 delivers conclusions, addresses the limitations of the methodology, and discusses further work.

## 2. Signature Transform

The Signature Transform [34–38] is roughly equivalent to the Fourier Transform; instead of extracting information concerning frequency, it extracts information about the order and area. However, the Signature Transform differs from the Fourier Transform in that it utilizes the space of functions of paths, a more general case than the basis of the space of paths found in the Fourier Transform.

Following the work in [34], the truncated signature of order  $N$  of the path  $\mathbf{x}$  is defined as a collection of coordinate iterated integrals

$$S^N(\mathbf{x}) = \left( \left( \int \cdots \int \prod_{c=1}^a \frac{df_{z_c}}{dt}(t_c) dt_1 \cdots dt_a \right)_{\substack{0 < t_1 < \cdots < t_a < 1 \\ 1 \leq z_1, \dots, z_a \leq d}} \right)_{1 \leq a \leq N}. \quad (1)$$

Here,  $\mathbf{x} = (x_1, \dots, x_n)$ , where  $x_z \in \mathbb{R}^d$ . Let  $f = (f_1, \dots, f_d): [0, 1] \rightarrow \mathbb{R}^d$  be continuous, such that  $f(\frac{z-1}{n-1}) = x_z$ , and linear in the intervals in between.

### 2.1. RMSE and MAE Signature and Log-Signature

The F1-score between a summary and the ground truth of annotated data has been the widely accepted measure of choice for the task of video summarization. However, recent approaches highlighted the need to come up with metrics that can capture the underlying nature of the information present in the video [31].

In this work, we leverage tools from harmonic analysis by the use of the Signature Transform to introduce a set of measures, namely, Signature and Log-Signature Root Mean Squared Error (denoted from now on as RMSE Signature and Log-Signature), that can shed light on what a good summary is and serve as powerful tools to analytically quantize the information present in the selected frames.

As introduced in [32] in the context of GAN convergence assessment, the RMSE and MAE Signature and Log-Signature can be defined as follows, particularized for the application under study:

**Definition 1.** Given  $n$  components of the element-wise mean of the signatures  $\{\tilde{y}^{(c)}\}_{c=1}^n \subseteq T(\mathbb{R}^d)$  from the target summary to the score, and the same number of components of the element-wise mean of the signatures  $\{\tilde{x}^{(c)}\}_{c=1}^n \subseteq T(\mathbb{R}^d)$  from the original video subsampled at a given frame rate and uniformly chosen, we define the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as

$$\text{RMSE}\left(\left\{\tilde{x}^{(c)}\right\}_{c=1}^n, \left\{\tilde{y}^{(c)}\right\}_{c=1}^n\right) = \sqrt{\frac{1}{n} \sum_{c=1}^n (\tilde{y}^{(c)} - \tilde{x}^{(c)})^2}, \quad (2)$$

and

$$\text{MAE}\left(\left\{\tilde{x}^{(c)}\right\}_{c=1}^n, \left\{\tilde{y}^{(c)}\right\}_{c=1}^n\right) = \frac{1}{n} \sum_{c=1}^n |\tilde{y}^{(c)} - \tilde{x}^{(c)}|, \quad (3)$$

respectively, where  $T(\mathbb{R}^d) = \Pi_{c=0}^{\infty}(\mathbb{R}^d)^{\otimes c}$ .

The case for Log-Signature is analogous.

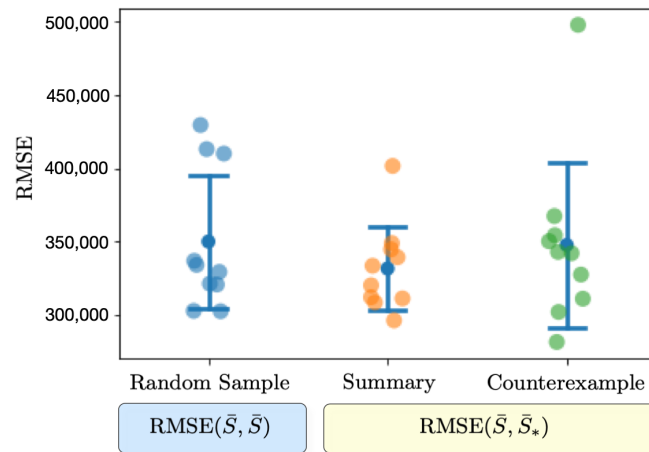
For the task of video summarization, two approaches are given. In the case where the user has annotated summaries available, RMSE ( $\tilde{S}, \tilde{S}_{target}$ ) is computed between an element-wise mean of the annotated summaries and the target summary to the score. If annotations are not available, a comparison against mean random uniform samples is performed,  $\tilde{S}$ , and mean score and standard deviation are provided. Given the properties of the Signature Transform, the measure takes into consideration the harmonic components that are intrinsic to the video under study and that should be preserved once the video is shortened to produce a summary. As a matter of fact, both approaches should lead to the same conclusions, as the harmonic components present in the annotated summaries and the ones present in average in the random uniform samples should also agree. A confidence interval of the scores can be provided for a given measure by analyzing the distances in the RMSEs of annotated summaries or random uniform samples, RMSE ( $\tilde{S}_a, \tilde{S}_c$ ).

When comparing against random uniform samples, the underlying assumption is as follows: we assume that good visual summaries capturing all or most of the harmonic components present in the visual cues will achieve a lower standard deviation. In contrast, summaries that lack support for the most important components will yield higher values. For a qualitative example, see Figure 1. With these ideas in mind, we can discern techniques that likely generate consistent summaries from those that fail to convey the most critical information. Moreover, the study of random sample intervals provides a set of tolerances for considering a given summary adequate for the task, meaning it is comparable to or better than uniform sampling of the interval at capturing harmonic components. Consequently, the proposed measures allow for a percentage score representing the number of times a given methodology outperforms random sampling by containing the same or more harmonic components present in the spectrum.

## 2.2. Summarization of Videos with RMSE Signature

Proposing a methodology based on the Signature Transform to select proper frames for a visual summary can be effectuated as follows: Given a uniform random sample of the video to summarize, we can compare it against subsequent random summaries using RMSE ( $\tilde{S}, \tilde{S}_*$ ). We can repeat this procedure  $n$  times and choose, as a good candidate, the minimum according to the standard deviation. Using this methodology, we can also repeat the procedure for a range of selected summary lengths, which will give us a set of good candidates, among which we will choose the candidate with the minimum standard deviation. This will provide us with an estimate of the most suitable length. It is important to note that this baseline is completely unsupervised in the sense that no annotations are used, only the metrics based on the Signature Transform. We rely on the fact that,

in general, uniform random samples provide relatively accurate summaries, and among those, we choose the ones that are best according to  $\text{std}(\text{RMSE}(\bar{S}, \bar{S}_*))$ , which we denote as  $\text{RMSE}(\bar{S}, \bar{S}_{u_{\min}})|_n$ . This will grant us competitive uniform random summaries according to the given measures to use as a baseline for comparison against other methodologies, and with which we can estimate an appropriate summary length to use in those cases.



**Figure 1.** Conceptual plot with  $\text{RMSE}(\bar{S}, \bar{S})$  and  $\text{RMSE}(\bar{S}, \bar{S}_*)$  standard deviation and mean for two given summaries (our method and a counterexample) of 12 frames using a randomly picked video from Youtube to illustrate how to select a proper summary according to the proposed metric.

Below, we provide a description of the entities involved in the computation of the metrics and the proposed baselines based on the Signature Transform:

- $\bar{S}_*$ : Element-wise mean Signature Transform of the target summary to the score of the corresponding video;
- $\bar{S}$ : Element-wise mean Signature Transform of a uniform random sample of the corresponding video;
- $\text{RMSE}(\bar{S}, \bar{S}_*)$ : Root mean squared error between the spectra of  $\bar{S}$  and  $\bar{S}_*$  with the same summary length. For the computation of standard deviation and mean, this value is calculated ten times, changing  $\bar{S}$ ;
- $\text{RMSE}(\bar{S}, \bar{S})$ : Root mean squared error between the spectra of  $\bar{S}$  and  $\bar{S}$  with the same summary length. For computation of standard deviation and mean, this value is calculated ten times, changing both  $\bar{S}$  each time;
- $\text{RMSE}(\bar{S}, \bar{S}_{u_{\min}})|_n$ : Baseline based on the Signature Transform. It corresponds to  $\text{RMSE}(\bar{S}, \bar{S}_*)$ , where  $\bar{S}_*$  is, in this case, a fixed uniform random sample denoted as  $\bar{S}_u$ . We repeat this procedure  $n$  times and choose the minimum candidate according to standard deviation,  $\bar{S}_{u_{\min}}$ , to propose as a summary;
- $\text{std}()$ : Standard deviation.

### 3. Summarization of Videos via Text-Conditioned Object Detection

Large Language Models (LLM) [39–42] and VLMs [43] have emerged as indispensable resources for characterizing complex tasks and bestowing intelligent systems with the capacity to interact with humans in unprecedented ways. These models, also called Foundation Models [44–46], excel in a wide variety of tasks, such as robotics manipulation [47–49], and can be integrated with other modules to perform robustly in highly complex situations such as navigation and guidance [50,51]. One fundamental module is the Vision Transformer [52].

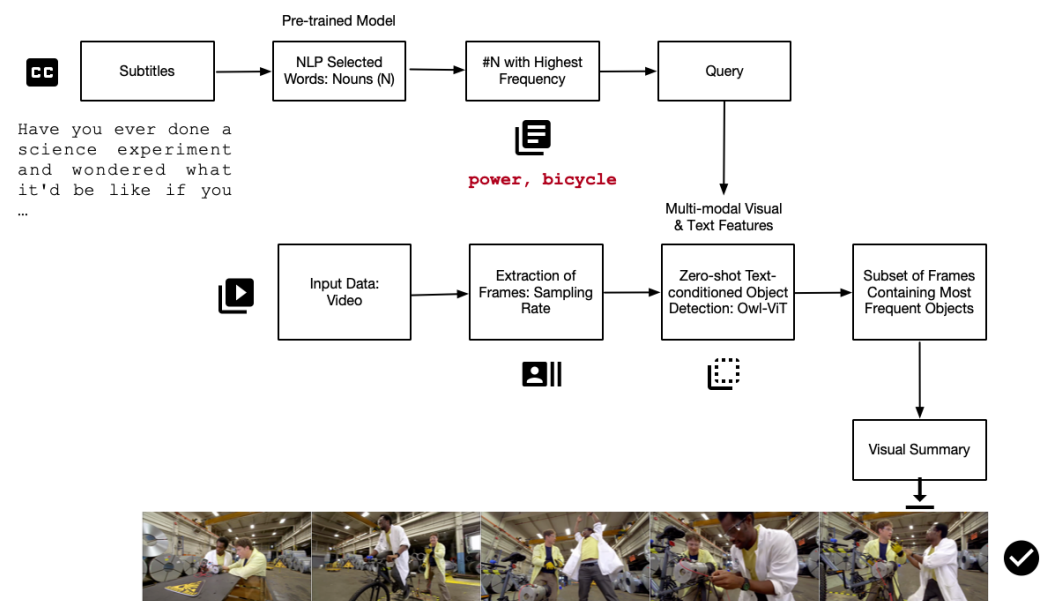
We introduce a simple yet effective technique aimed at generating video summaries that accurately describe the information contained within video streams, while also proposing new measures for the task of the summarization of videos. These measures will prove



useful not only when text transcriptions are available, but also in more general cases in which we seek to describe the quality of a video summary.

Building on the text-conditioned object detection using Vision Transformers, as recently proposed in [53], we enhance the summarization task by leveraging the automated text transcriptions found in video platforms. We utilize a module of noun extraction employing NLP techniques [54], which is subsequently processed to account for the most frequent nouns. These nouns serve as input queries for text-conditioned object searches in frames. Frames containing the queries are selected for the video summary; see Figure 2 for a detailed depiction of the methodology.

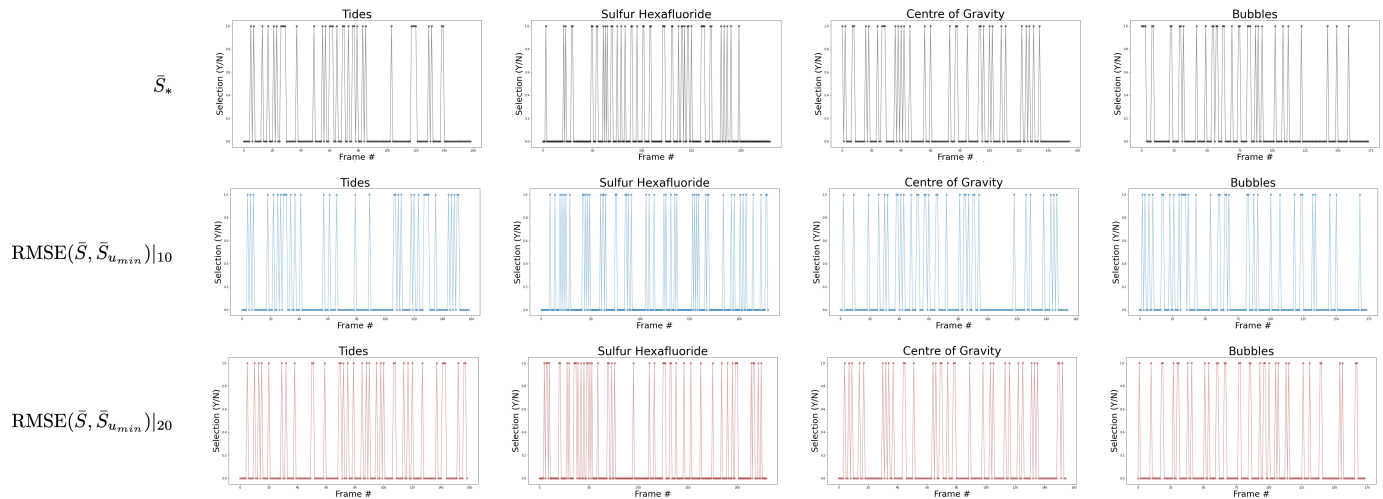
In this manuscript, we initially present a baseline leveraging text-conditioned object detection, specifically Contrastive Language–Image Pre-training (CLIP) [43]. To assess this approach, we employ a recently introduced metric based on the Signature Transform, which accurately gauges summary quality compared to a uniform random sample. Our preliminary baseline effectively demonstrates the competitiveness of uniform random sampling [31]. Consequently, we introduce a technique utilizing prior knowledge of the Signature, specifically the element-wise mean comparison of the spectrum, to generate highly accurate random uniform samples for summarization. The Signature Transform allows for a design featuring an inherent link between the methodology, metric, and baseline. We first present a method for evaluation, followed by a set of metrics for assessment, and ultimately, we propose a state-of-the-art baseline that can function as an independent technique.



**Figure 2.** Video Summarization via Zero-shot Text-conditioned Object Detection.

#### 4. Experiments: Dataset and Metrics

A dataset consisting of 28 videos about science experiments was sourced from Youtube, along with their automatic audio transcriptions, to evaluate the methodology and the proposed metrics. Table 1 provides a detailed description of the collected data and computed metrics, Figure 3 shows the distribution of selected frames using text-conditioned object detection over a subset of videos and the baselines based on the Signature Transform, Figure 4 depicts a visual comparison between methodologies, and Figures 5 and 6 visually elucidate the RMSE distribution for each video with mean and standard deviation.



**Figure 3.** Comparison of distribution of selected frames for a subset of videos (Tides, Sulfur Hexafluoride, Centre of Gravity and Bubbles) using the method based on text-conditioned object detection and the baselines using the Signature Transform.

The dataset consists of science videos covering a wide range of experiments on several topics of interest; it has an average number of 264 frames per video (sampling rate  $\frac{1}{4}$  s) and an average duration of 17 min 30 s.

Figure 3 depicts the selected frames when using our methodology for a subset of videos in the dataset. The selection coincides with the trigger of the zero-shot text-conditioned object detector by the 20 most frequent word code-phrase queries, which chooses a subset of the methodology that best explains the main factors of the argument. A comparison with the baselines based on the Signature Transform with 10 and 20 points is delivered.

In all experiments that involve the computation of the Signature Transform, we use the parameters proposed in [32] that were originally used to assess synthetic distributions generated with GANs; specifically, we employ truncated signatures of order 3 with a resized image size of  $64 \times 64$  in grayscale.

$\text{RMSE}(\bar{S}, \bar{S}_*)$  computes the element-wise mean of the signatures of both the target summary to the score and a random uniform sample with the same number of frames, comparing their spectra with the use of the RMSE. Likewise,  $\text{RMSE}(\bar{S}, \bar{S})$  computes the same measure between two random uniform samples with the same number of frames. The standard deviation of both results is compared to assess the quality of the summarized video concerning the present harmonic components. The preliminary technique based on text-conditioned object detection (see Table 1) achieves a zero-shot of 50% positive cases when compared against std ( $\text{RMSE}(\bar{S}, \bar{S})$ ). The number of frames selected by the methodology is consistent, and it automatically selects on average 20% of the total number of frames.

In this paragraph, we discuss the baseline based on the Signature Transform (see Table 1) in terms of the  $\text{RMSE}(\bar{S}, \bar{S}_{u_{min}})|_{10}$  and  $\text{RMSE}(\bar{S}, \bar{S}_{u_{min}})|_{20}$ . These techniques select a uniform random sample with minimum standard deviation in a set of 10 points and 20 points, respectively, and achieve 100% positive cases when compared to  $\text{RMSE}(\bar{S}, \bar{S})$ . Under the assumption that the summary can be approximated well by a random uniform sample, which holds true in many cases, the methodology finds a set of frames that maximizes the harmonic components relative to those present in the original video.

**Table 1.** Descriptive statistics with RMSE ( $\bar{S}, \bar{S}_*$ ) (target summary against random uniform sample) and RMSE ( $\bar{S}, \bar{S}$ ) (random uniform sample against random uniform sample). RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ) and RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{20}$ ) correspond to the baselines based on the Signature Transform using 10 and 20 random samples, respectively. Highlighted results in blue/brown correspond to values better than std (RMSE ( $\bar{S}, \bar{S}$ )). Yellow values indicate when std (RMSE ( $\bar{S}, \bar{S}$ )) is lower than std (RMSE ( $\bar{S}, \bar{S}_*$ )).

Descriptive Statistics			Summary	RMSE ( $\bar{S}, \bar{S}_*$ )		RMSE ( $\bar{S}, \bar{S}$ )		RMSE ( $\bar{S}, \bar{S}_{u_{min}} _{10}$ )		RMSE ( $\bar{S}, \bar{S}_{u_{min}} _{20}$ )	
Video	# Frames	Length	# Frames (%)	Std	Mean	Std	Mean	Std	Mean	Std	Mean
Tides	159	10 m 29 s	35 (22%)	13,663	202,388	14,838	155,986	8859	157,455	7312	167,480
Sulfur Hexafluoride	230	15 m 12 s	47 (20%)	22,727	217,935	22,607	179,409	7194	161,995	7722	173,490
Centre of Gravity	155	10 m 14 s	33 (21%)	12,333	181,460	16,404	168,824	8481	160,779	12,416	175,971
Bubbles	174	11 m 30 s	35 (20%)	23,127	201,553	16,806	185,702	7461	194,993	5711	175,176
Airplanes	158	10 m 24 s	22 (14%)	19,964	215,688	23,591	231,539	8417	227,391	10,235	233,020
Protons	174	11 m 30 s	25 (14%)	29,853	252,224	20,186	262,434	12,835	251,907	11,542	250,512
Hydrophobic	168	11 m 06 s	29 (17%)	15,016	251,671	25,835	248,548	11,973	250,131	13,917	245,761
States of Matter	332	22 m 03 s	78 (23%)	16,249	156,408	9709	130,064	6630	115,454	5340	121,028
Spool Racer	332	22 m 02 s	90 (27%)	15,903	142,520	11,883	136,147	7054	137,621	8112	151,888
Paper Airplane	332	22 m 03 s	29 (9%)	20,642	235,639	11,829	221,220	5400	224,718	9385	177,448
Loudest Sound	332	22 m 01 s	93 (28%)	16,898	179,963	8304	148,885	7884	138,561	4355	147,016
Lightning	332	22 m 01 s	70 (21%)	15,237	169,338	21,862	162,849	9300	177,008	7494	153,797
Light Challenge	332	22 m 02 s	82 (25%)	12,566	152,488	10,546	126,117	5490	139,700	4874	129,044
Hot Air Balloon	332	22 m 01 s	98 (30%)	8620	150,366	5417	144,634	3516	137,141	4165	138,453
Hoop Glider	332	22 m 01 s	82 (25%)	6419	148,065	6752	132,544	4051	133,897	4966	133,894
Drag Race	332	22 m 03 s	73 (22%)	9384	135,228	8931	125,264	4375	122,615	4645	129,851
All about Balance	332	22 m 03 s	59 (18%)	14,023	182,063	14,238	182,179	7801	176,219	6914	167,727
Air Pressure	332	22 m 03 s	65 (20%)	10,123	166,342	18,314	151,664	6386	145,897	4602	148,232
Friction and Momentum	162	10 m 42 s	28 (17%)	18,754	217,403	22,443	218,203	13,348	202,288	12,238	205,680
Electricity	162	10 m 41 s	30 (19%)	24,376	298,238	22,885	279,820	16,889	268,932	10,263	270,619
Catapult	169	11 m 11 s	27 (16%)	26,413	271,643	31,265	214,727	15,158	203,290	10,222	188,008
Carbonation and More	165	10 m 53 s	40 (24%)	18,977	237,142	18,107	226,044	12,130	234,278	11,884	214,149
Carbon Dioxide	162	10 m 41 s	38 (23%)	25,862	245,415	18,806	217,270	13,838	207,828	7760	211,504
Bridge	164	10 m 51 s	21 (13%)	25,839	269,412	26,038	271,551	10,761	263,747	13,038	264,532
Bread Experiment	337	22 m 22 s	59 (18%)	15,099	189,086	8575	146,771	5542	153,224	5691	156,230
Balloon Power	337	22 m 22 s	53 (16%)	14,075	157,542	29,415	147,710	7741	128,920	7351	134,545
Attraction and Forces	654	43 m 30 s	81 (12%)	5955	107,097	7486	102,965	3701	96,266	2093	99,271
Puzzles	209	13 m 48 s	46 (22%)	11,258	185,502	19,012	196,762	14,620	199,556	14,622	197,064
Average	264	17 m 30 s	52 (20%)	14/28 (50%)				28/28 (100%)		28/28 (100%)	

Figure 4 displays examples of summaries using the baseline based on the Signature Transform compared to the summaries using text-conditioned object detection. The figure allows for a visual comparison of the results obtained using RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ), RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{20}$ ) and  $\bar{S}_*$ . The best summary among the three baselines according to the metric is highlighted (Table 1).



**Figure 4.** Summarization of videos using the baseline based on the Signature Transform in comparison to the summarization using text-conditioned object detection. RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ), RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{20}$ ) and  $\bar{S}_*$  summaries for two videos of the introduced dataset. The best summary among the three, according to the metric, is highlighted.

The selected frames are consistent and provide a good overall description of the original videos. Moreover, the metric based on the Signature Transform aligns well with our expectations of a high-quality summary, with better scores being assigned to summaries that effectively convey the content present in the original video.

Table 2 presents a qualitative analysis of the baseline based on the Signature Transform using 10 points, RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ) and RMSE ( $\bar{S}, \bar{S}$ ) with a varying number of frames per summary. We observe that RMSE ( $\bar{S}, \bar{S}$ ) reflects the variability of the harmonic compo-

nents present; that is, it is preferable to work with lengths for which the variability among summaries is low, according to the standard deviation.  $RMSE(\bar{S}, \bar{S}_{u_{min}})|_{10}$  indicates the minimum standard deviation achieved in a set of 10 points, meaning that given a computational budget allowing us to select up to a specific number of frames, a good choice is to pick the length that yields the minimum  $RMSE(\bar{S}, \bar{S}_{u_{min}})|_{10}$  with low variability, as per  $RMSE(\bar{S}, \bar{S})$ .

$RMSE(\bar{S}, \bar{S}_*)$  (Figure 5) and  $RMSE(\bar{S}, \bar{S})$  (Figure 6) show the respective distribution of RMSE values (10 points) with the mean and standard deviation. Low standard deviations, in comparison with the random uniform sample counterparts, indicate good summarization capabilities.

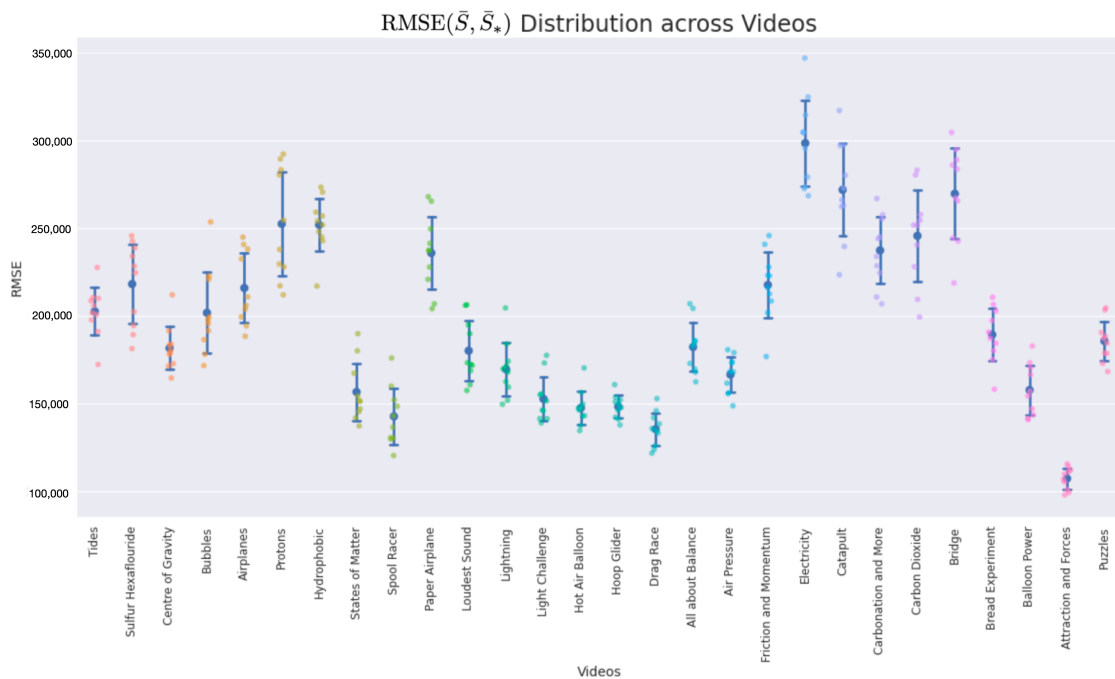


Figure 5. Plot with  $RMSE(\bar{S}, \bar{S}_*)$  standard deviation and mean.

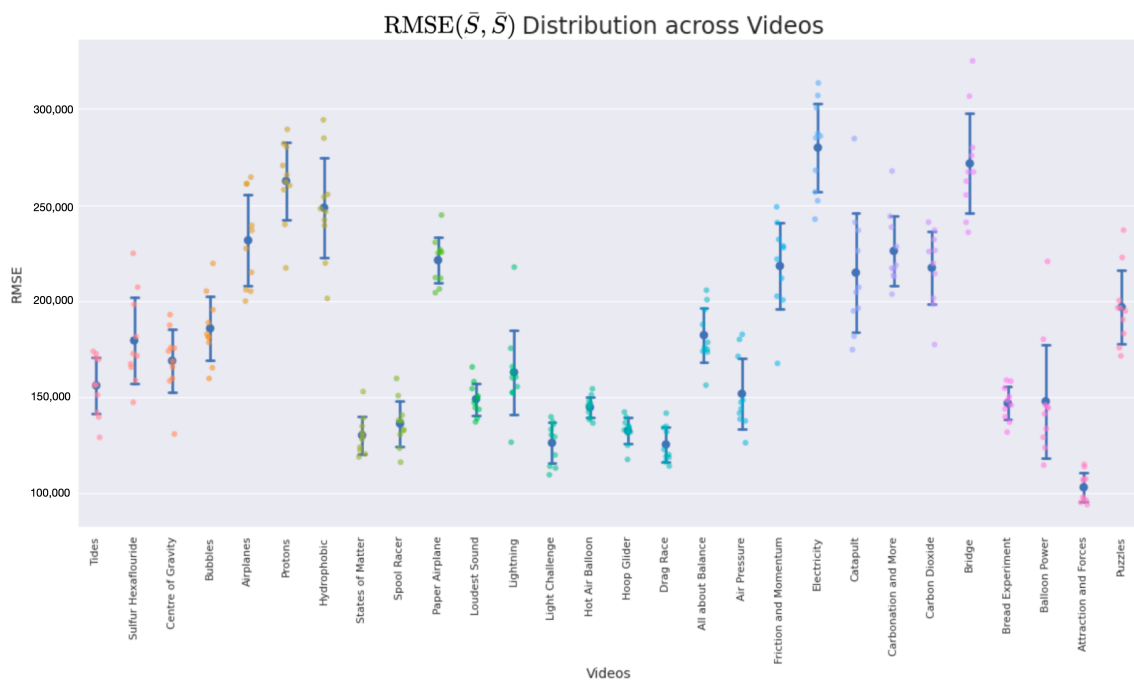
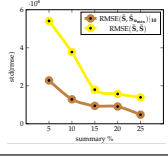
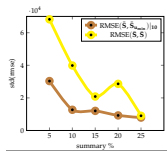
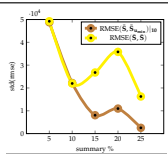
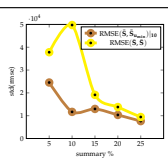


Figure 6. Plot with  $RMSE(\bar{S}, \bar{S})$  standard deviation and mean.

**Table 2.** Descriptive statistics for a set of videos with varying numbers of frames per summary with RMSE  $(\bar{S}, \bar{S}_{u_{min}})_{|10}$  (brown) and RMSE  $(\bar{S}, \bar{S})$  (yellow).

Dataset			RMSE $(\bar{S}, \bar{S}_{u_{min}}) _{10}$		RMSE $(\bar{S}, \bar{S})$		Visualization
Video	# Frames	Summary (%)	Std	Mean	Std	Mean	Plot (Std,Std)
Tides	159	8 (5%)	22,786	422,026	54,067	390,483	
		16 (10%)	12,851	254,984	37,713	263,881	
		24 (15%)	9423	202,925	17,935	224,797	
		32 (20%)	9074	183,933	15,700	186,621	
		40 (25%)	4782	158,183	13,903	159,452	
Sulfur Hexafluoride	230	12 (5%)	30,325	452,134	68,212	362,061	
		23 (10%)	12,701	281,425	39,872	246,967	
		35 (15%)	12,034	228,530	20,846	201,740	
		46 (20%)	9241	190,985	28,621	175,440	
		58 (25%)	7914	161,618	9021	152,310	
Centre of Gravity	155	8 (5%)	48,787	406,502	49,234	369,648	
		16 (10%)	22,163	252,841	21,974	276,366	
		24 (15%)	8050	212,893	26,776	229,959	
		31 (20%)	10,963	180,953	35,813	184,437	
		39 (25%)	2528	164,666	16,259	163,007	
Bubbles	174	9 (5%)	24,538	401,406	37,816	397,470	
		18 (10%)	11,669	272,430	49,740	276,152	
		27 (15%)	12,965	213,336	19,125	215,961	
		35 (20%)	10,331	190,639	13,792	183,984	
		44 (25%)	7625	173,009	9427	162,091	

#### 4.1. Assessment of the Metrics

The metrics have been rigorously evaluated using the dataset in [1], which consists of short videos sourced from Youtube, and includes 5 annotated summaries per video for a total of 20. Tables 3 and 4 report the results, using a one-frame-per-second sampling rate. In this case, the average number of times that the human annotator outperforms uniform random sampling according to the proposed metric, std (RMSE  $(\bar{S}, \bar{S})$ ), is 87%. Several observations emerge from these findings:

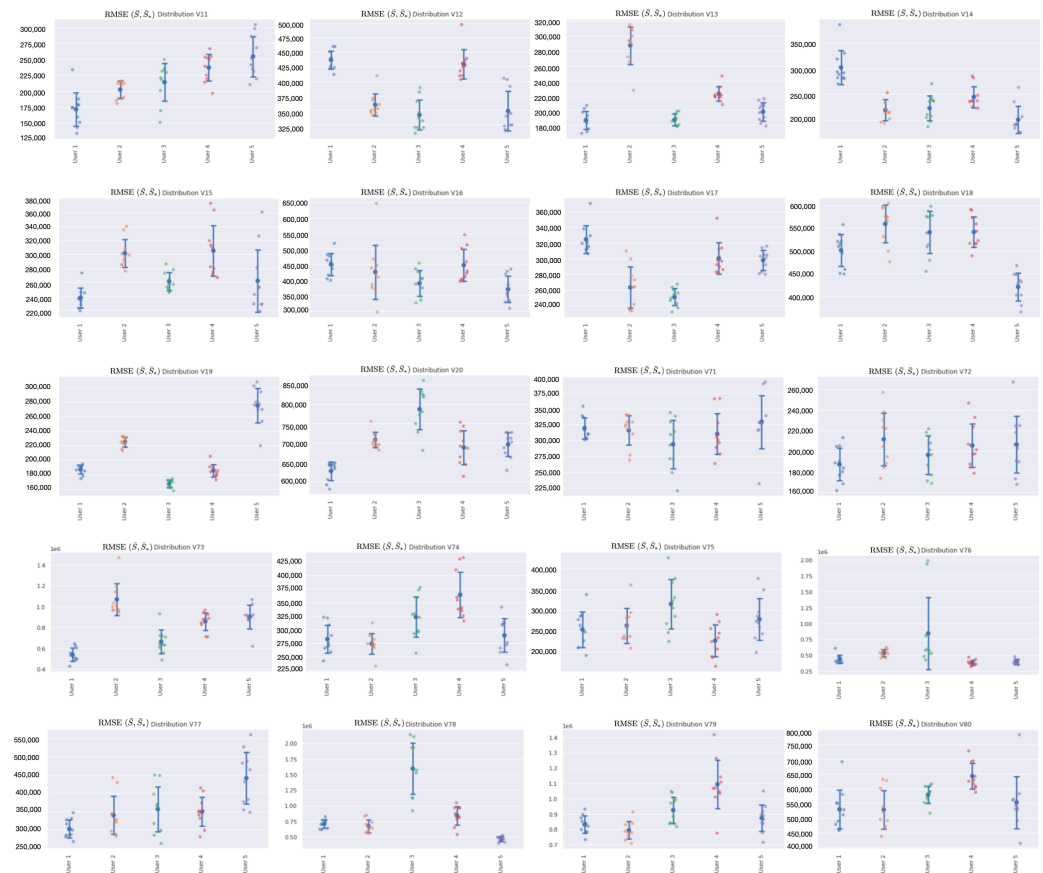
- The proposed metrics demonstrate that human evaluators can perform above average during the task, effectively capturing the dominant harmonic frequencies present in the video.
- Another crucial aspect to emphasize is that the metrics are able to evaluate human annotators with fair criteria and identify which subjects are creating competitive summaries.
- Moreover, the observations from this study indicate that the metrics serve as a reliable proxy for evaluating summaries without the need for annotated data, as they correlate strongly with human annotations.

Figure 7 shows the mean and standard deviation for each human-annotated summary (user 1 to user 5) for the subset of 20 videos from [1], using a sampling rate of 1 frame per second. For each video, a visual inspection of the error plot bar for each annotated summary provides an accurate estimate of the quality of the annotation compared to other users. Specifically:

- Annotations with lower standard deviations offer a better harmonic representation of the overall video;
- Annotations with higher standard deviations suggest that important harmonic components are missing from the given summary;
- The metrics make it simple to identify annotated summaries that may need to be relabeled for improved accuracy.

Furthermore, these metrics remain consistent when applied to various sampling rates.





**Figure 7.** Error bar plot with mean and standard deviation for each human-annotated summary of the subset of 20 videos from [1]. Sampling rate: 1 frame per second.

That being said, there are several standard measures that are commonly used for video summarization, such as F1 score, precision, recall, and Mean Opinion Score (MOS). Each of these measures has its own strengths and weaknesses. Compared to these standard measures, the proposed benchmark based on the Signature Transform has several potential advantages. Here are a few reasons for this:

- **Content based:** the Signature Transform is a content-based approach that captures the salient features of the video data. This means that the proposed measure is not reliant on manual annotations or subjective human ratings, which can be time consuming and prone to biases.
- **Robustness:** the Signature Transform is a robust feature extraction technique that can handle different types of data, including videos with varying frame rates, resolutions, and durations. This means that the proposed measure can be applied to a wide range of video datasets without the need for pre-processing or normalization.
- **Efficiency:** the Signature Transform is a computationally efficient approach that can be applied to large-scale datasets. This means that the proposed measure can be used to evaluate the effectiveness of visual summaries quickly and accurately.
- **Flexibility:** the Signature Transform can be applied to different types of visual summaries, including keyframe-based and shot-based summaries. This means that the proposed measure can be used to evaluate different types of visual summaries and compare their effectiveness.

Overall, the proposed measure based on the Signature Transform has the potential to provide a more accurate and comprehensive assessment of the standard of visual summaries compared to the preceding measures used in video summarization.



**Table 3.** Descriptive statistics with RMSE ( $\bar{S}, \bar{S}_*$ ) (target summary against random uniform sample) and RMSE ( $\bar{S}, \bar{S}$ ) (random uniform sample against random uniform sample). Lower is better. Sampling rate: 1 frame per second. Dataset in [1], videos from V11 to V20. Highlighted results in blue/yellow correspond to the lowest values, either std (RMSE ( $\bar{S}, \bar{S}_*$ )) or std (RMSE ( $\bar{S}, \bar{S}$ )), respectively.

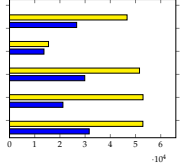
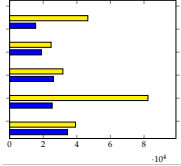
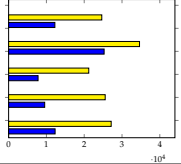
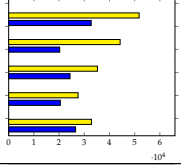
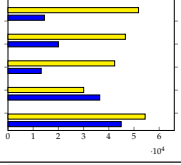
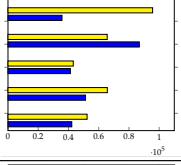
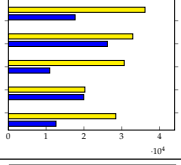
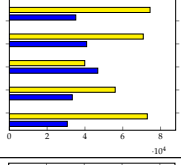
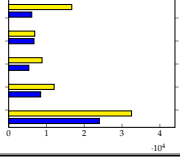
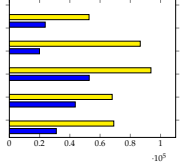
Youtube, Dataset				RMSE ( $\bar{S}, \bar{S}_*$ )		RMSE ( $\bar{S}, \bar{S}$ )		Visualization
Video	# Frames	User	# Frames User	Std	Mean	Std	Mean	Plot (Std, Std)
V11	48	1	10	26,644	171,106	46,655	151,483	
		2	12	13,673	202,172	15,479	155,481	
		3	10	29,857	213,880	51,590	182,327	
		4	9	21,192	236,959	52,982	196,303	
		5	8	31,627	254,336	52,925	193,520	
V12	59	1	11	15,497	436,723	46,551	252,142	
		2	17	18,927	359,562	24,665	177,286	
		3	15	26,071	342,161	31,703	180,066	
		4	11	25,330	429,272	82,323	242,627	
		5	14	34,479	348,834	39,199	188,417	
V13	59	1	19	12,238	187,001	24,649	114,155	
		2	9	25,267	287,479	34,635	166,495	
		3	18	7790	187,346	21,203	126,432	
		4	14	9544	222,496	25,553	140,508	
		5	18	12,298	198,349	27,138	124,386	
V14	59	1	9	32,739	302,118	51,770	183,978	
		2	16	20,249	219,068	44,235	141,927	
		3	17	24,345	222,559	35,235	113,806	
		4	10	20,498	244,509	27,548	155,515	
		5	16	26,561	200,139	32,840	143,384	
V15	57	1	12	14,454	237,551	51,812	207,845	
		2	11	20,018	301,650	46,590	209,491	
		3	13	13,192	261,014	42,337	171,810	
		4	13	36,408	305,376	30,041	179,442	
		5	14	44,931	261,859	54,428	180,145	
V16	70	1	9	35,722	449,758	95,662	376,411	
		2	9	86,863	425,107	65,626	328,563	
		3	12	41,260	388,869	43,186	340,133	
		4	9	51,299	447,523	65,698	375,162	
		5	13	42,200	369,517	52,316	302,677	
V17	59	1	12	17,668	324,562	36,166	242,235	
		2	13	26,203	262,895	32,930	243,366	
		3	18	10,957	250,543	30,660	177,779	
		4	12	19,956	300,390	20,252	223,791	
		5	16	12,611	297,707	28,433	207,258	
V18	50	1	13	35,152	501,230	74,454	260,574	
		2	14	40,896	559,244	70,863	274,572	
		3	14	46,791	540,747	39,899	246,964	
		4	10	33,309	541,490	56,012	329,343	
		5	14	30,663	420,924	72,998	308,756	
V19	65	1	15	6114	186,893	16,695	119,136	
		2	20	6701	225,075	6899	103,517	
		3	20	5339	167,085	8834	103,752	
		4	13	8462	185,452	12,020	129,608	
		5	6	23,992	275,155	32,512	208,629	

Table 3. Cont.

Youtube, Dataset				RMSE ( $\bar{S}$ , $\bar{S}_*$ )		RMSE ( $\bar{S}$ , $\bar{S}$ )		Visualization
Video	# Frames	User	# Frames User	Std	Mean	Std	Mean	Plot (Std,Std)
V20	61	1	15	23,716	627,121	52,711	540,857	
		2	12	19,933	707,823	86,586	609,589	
		3	9	52,818	787,188	93,656	747,199	
		4	11	43,598	688,065	68,016	617,091	
		5	11	31,058	695,905	69,077	618,156	

**Table 4.** Descriptive statistics with RMSE ( $\bar{S}$ ,  $\bar{S}_*$ ) (target summary against random uniform sample) and RMSE ( $\bar{S}$ ,  $\bar{S}$ ) (random uniform sample against random uniform sample). Lower is better. Sampling rate: 1 frame per second. Dataset in [1], videos from V71 to V80. Highlighted values correspond to the lowest standard deviation.

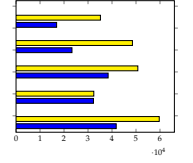
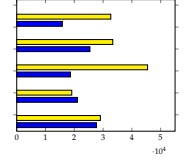
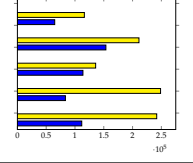
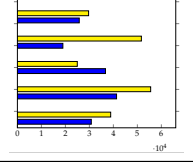
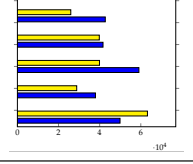
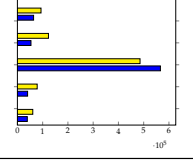
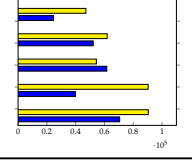
Youtube, Dataset				RMSE ( $\bar{S}$ , $\bar{S}_*$ )		RMSE ( $\bar{S}$ , $\bar{S}$ )		Visualization
Video	# Frames	User	# Frames User	Std	Mean	Std	Mean	Plot (Std,Std)
V71	277	1	18	16,916	319,975	35,173	330,114	
		2	18	23,314	315,996	48,511	339,793	
		3	20	38,384	293,853	50,766	345,021	
		4	17	32,270	310,193	32,411	359,049	
		5	18	41,753	329,353	59,688	334,337	
V72	536	1	18	15,842	187,019	32,676	194,820	
		2	16	25,427	211,466	33,363	202,442	
		3	16	18,684	196,149	45,453	217,699	
		4	18	21,112	205,421	19,122	177,117	
		5	18	27,718	206,335	29,057	205,808	
V73	201	1	11	64,802	538,239	116,284	484,970	
		2	7	153,682	106,8305	211,124	704,655	
		3	8	113,805	661,992	135,899	653,041	
		4	8	83,387	856,406	248,619	689,301	
		5	7	111,767	899,150	241,947	794,828	
V74	293	1	17	25,780	282,200	29,674	309,051	
		2	16	18,954	273,776	51,670	331,322	
		3	15	36,714	322,833	24,961	335,618	
		4	13	41,327	363,665	55,543	369,875	
		5	16	30,798	289,135	38,881	353,928	
V75	383	1	14	42,736	254,385	25,959	282,877	
		2	13	41,632	263,431	39,826	337,124	
		3	10	59,083	315,531	39,925	330,766	
		4	17	37,954	227,411	28,843	250,314	
		5	12	49,908	278,966	63,236	312,366	
V76	89	1	6	64,097	440,825	93,524	422,565	
		2	4	53,727	536,138	123,009	464,922	
		3	1	566,208	843,799	485,614	878,793	
		4	6	40,356	382,643	78,354	424,418	
		5	6	39,194	395,906	60,916	401,751	
V77	168	1	12	24,546	302,076	47,095	366,748	
		2	9	52,176	339,285	61,880	385,056	
		3	9	61,623	355,883	54,390	413,118	
		4	10	39,765	349,207	90,313	400,379	
		5	7	70,562	440,656	90,468	451,833	

Table 4. Cont.

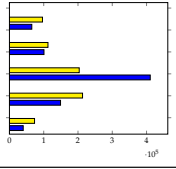
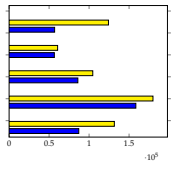
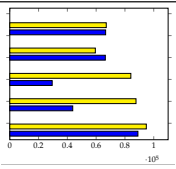
Youtube, Dataset				RMSE ( $\bar{S}, \bar{S}_*$ )		RMSE ( $\bar{S}, \bar{S}$ )		Visualization
Video	# Frames	User	# Frames User	Std	Mean	Std	Mean	Plot (Std, Std)
V78	310	1	13	65,238	706,978	96,368	770,000	
		2	14	100,771	672,121	112,412	807,250	
		3	3	410,792	159,3229	203,589	188,2757	
		4	9	149,063	839,743	213,286	106,1204	
		5	23	40,178	466,571	73,228	614,140	
V79	49	1	7	56,918	831,057	124,249	835,575	
		2	8	56,569	793,831	60,657	859,241	
		3	6	85,973	925,025	104,621	990,479	
		4	5	158,480	109,3141	179,902	109,9105	
		5	6	87,104	873,950	131,597	895,318	
V80	159	1	18	66,585	529,875	67,019	572,836	
		2	17	66,367	527,930	59,432	602,819	
		3	13	29,459	579,078	84,101	726,883	
		4	12	43,740	643,016	87,688	685,117	
		5	14	89,016	553,274	94,849	649,317	

Figure 8 shows a summary that is well annotated by all users, demonstrating that the metrics can accurately indicate when human annotators have effectively summarized the information present in the video.

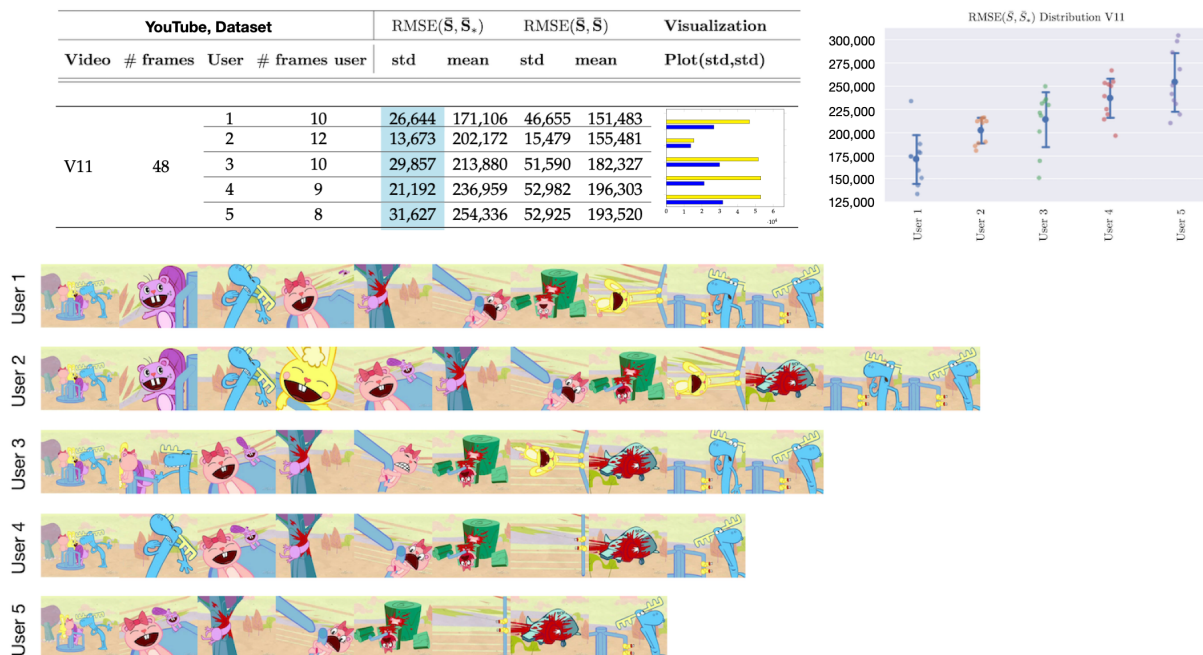
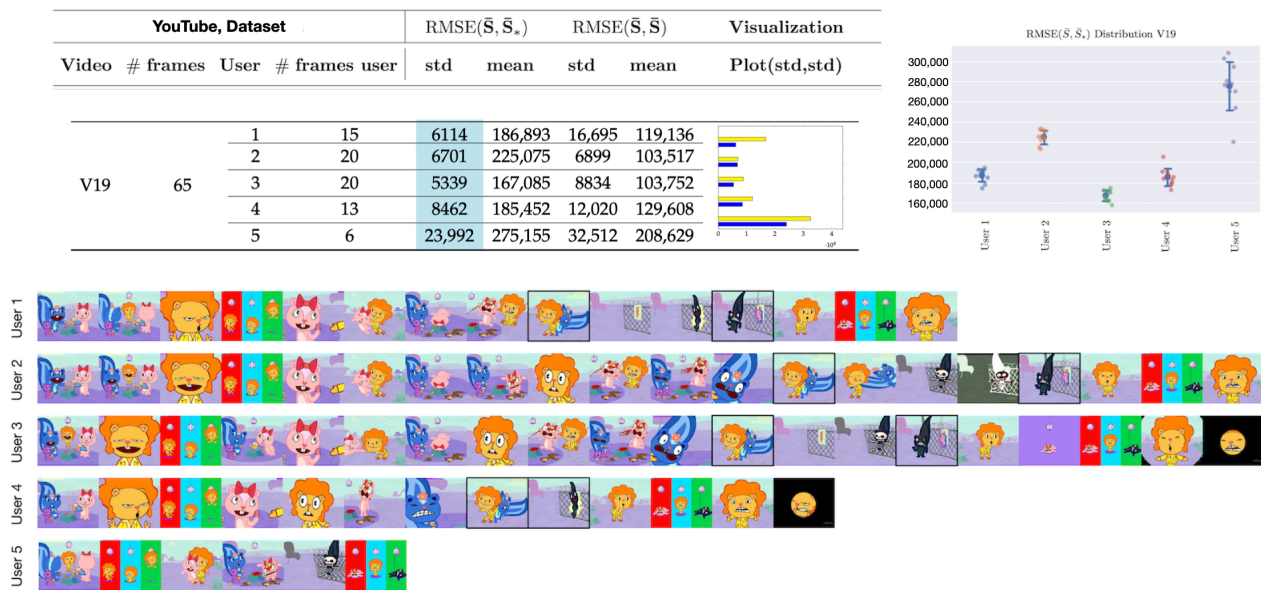


Figure 8. Visual depiction of human annotated summaries together with RMSE ( $\bar{S}, \bar{S}_*$ ) and RMSE ( $\bar{S}, \bar{S}$ ) of video V11, Table 3. Sampling rate: 1 frame per second. Highlighted values on the table correspond to the lowest standard deviation.

To illustrate how these metrics can help improve annotations, Figure 9 displays the metrics along with the annotated summaries of users 1 to 5. We observe that selecting the frames highlighted by users 1–4 can increase the performance if user 5 is asked to relabel its summary.



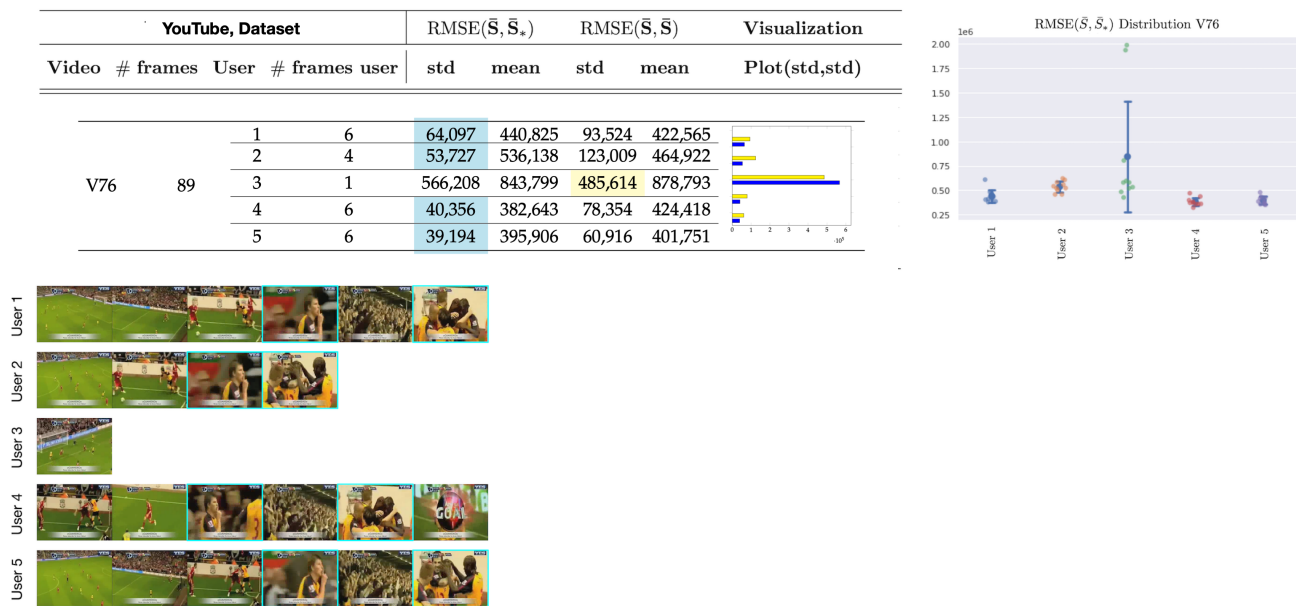
**Figure 9.** Visual depiction of human annotated summaries together with RMSE ( $\bar{S}, \bar{S}_*$ ) and RMSE ( $\bar{S}, \bar{S}$ ) of video V19, Table 3. Sampling rate: 1 frame per second. Highlighted frames can increase the accuracy of the annotated summary by user 5. Highlighted values on the table correspond to the lowest standard deviation.

Figure 10 showcases an example in which random uniform sampling outperforms the majority of human annotators. This occurs because the visual information is uniformly distributed throughout the video. In this case, user 5 performs the best, scoring slightly higher than std (RMSE ( $\bar{S}, \bar{S}$ )). Highlighted values on the table correspond to the lowest standard deviation.



**Figure 10.** Visual depiction of human annotated summaries, together with RMSE ( $\bar{S}, \bar{S}_*$ ) and RMSE ( $\bar{S}, \bar{S}$ ) of video V75, Table 4. Sampling rate: 1 frame per second. Highlighted values on the table correspond to the lowest standard deviation.

Similarly, Figure 11 presents an example in which incorporating the highlighted frames improves the accuracy of the annotated summary by user 3, which is currently performing worse than uniform random sampling, according to the metrics.



**Figure 11.** Visual depiction of human annotated summaries together with RMSE ( $\bar{S}, \bar{S}_*$ ) and RMSE ( $\bar{S}, \bar{S}$ ) of video V76, Table 4. Sampling rate: 1 frame per second. Highlighted frames can increase the accuracy of the annotated summary by user 3. Highlighted values on the table correspond to the lowest standard deviation.

#### 4.2. Evaluation

In this section, we evaluate the baselines and metrics compared to VSUMM [1], a methodology based on handcrafted techniques that performs particularly well on this dataset. Table 5 displays the comparison between the standard deviation of RMSE ( $\bar{S}, \bar{S}_*$ ) and RMSE ( $\bar{S}, \bar{S}$ ), as well as against the baselines based on the Signature Transform, RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ) and RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{20}$ ), with 10 and 20 points, respectively.

We can observe how the metrics effectively capture the quality of the visual summaries and how the introduced methodology based on the Signature Transform achieves state-of-the-art results with both 10 and 20 points. The advantages of using a technique that operates on the spectrum of the signal, compared to other state-of-the-art systems, is that it can generate visual summaries without fine-tuning the methodology. In other words, there is no need to train on a subset of the target distribution of videos, but rather, compelling summaries can be generated at once for any dataset. Moreover, this approach is highly efficient, as computation is performed on the CPU and consists only of calculating the Signature Transform, element-wise mean, and RMSE. These operations can be further optimized for rapid on-device processing or for deploying in parallel at the tera-scale level.

**Table 5.** VSUMM [1] comparison against baseline based on the Signature Transform for the first 20 videos of the dataset crawled from Youtube. Descriptive statistics with RMSE ( $\bar{S}, \bar{S}_*$ ) (target summary against random uniform sample) and RMSE ( $\bar{S}, \bar{S}$ ) (random uniform sample against random uniform sample). RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{10}$ ) and RMSE ( $\bar{S}, \bar{S}_{u_{min}}|_{20}$ ) correspond to the baselines based on the Signature Transform using 10 and 20 random samples, respectively. Highlighted results are better than std (RMSE ( $\bar{S}, \bar{S}$ )). Sampling rate: 1 frame per second. Highlighted results correspond to lowest standard deviation as described in Table 1.

Descriptive Statistics			VSUMM		RMSE ( $\bar{S}, \bar{S}_*$ )		RMSE ( $\bar{S}, \bar{S}$ )		RMSE ( $\bar{S}, \bar{S}_{u_{min}} _{10}$ )		RMSE ( $\bar{S}, \bar{S}_{u_{min}} _{20}$ )	
Video	# Frames	# Frames	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean
V11	48	11	25,981	185,959	37,907	175,031	16,343	148,128	18,343	159,157		
V12	59	13	56,274	313,156	41,613	205,004	17,770	181,533	11,665	206,951		
V13	59	19	7018	184,865	15,319	120,307	10,578	110,258	6655	134,846		
V14	59	8	21,415	281,969	39,412	171,935	19,069	157,531	10,104	180,199		
V15	57	10	20,159	271,197	46,041	219,182	27,536	192,667	27,765	218,787		



Table 5. Cont.

Descriptive Statistics		VSUMM	RMSE ( $\tilde{S}$ , $\tilde{S}_*$ )		RMSE ( $\tilde{S}$ , $\tilde{S}$ )		RMSE ( $\tilde{S}$ , $\tilde{S}_{u_{min}}$ ) <sub>10</sub>		RMSE ( $\tilde{S}$ , $\tilde{S}_{u_{min}}$ ) <sub>20</sub>	
Video	# Frames	# Frames	Std	Mean	Std	Mean	Std	Mean	Std	Mean
V16	70	9	65,997	513,440	84,667	428,025	38,088	283,324	30,235	446,068
V17	59	15	10,697	255,666	41,831	197,136	17,625	197,944	19,102	227,646
V18	50	14	42,731	449,324	51,635	230,695	33,525	261,288	30,179	242,746
V19	65	16	3891	235,797	5739	121,766	5883	116,245	4582	111,766
V20	61	9	43,864	796,448	39,035	733,547	28,460	684,546	39,414	644,681
V71	277	17	20,840	383,945	43,176	341,779	14,908	352,365	20,657	327,732
V72	536	12	61,886	233,649	48,603	252,688	17,604	276,631	18,966	248,489
V73	201	10	40,261	717,107	156,051	533,457	64,344	681,064	38,361	711,039
V74	293	17	26,274	270,374	36,674	334,265	17,622	354,621	17,486	330,606
V75	383	10	37,516	272,804	38,026	366,510	23,163	339,078	21,295	360,216
V76	89	7	36,084	353,323	114,266	377,699	31,131	335,958	34,724	405,954
V77	168	9	26,653	361,516	67,134	422,612	33,214	407,085	27,562	480,795
V78	310	13	95,305	831,043	127,705	823,938	33,903	980,397	36,361	951,784
V79	49	7	67,052	965,267	101,325	878,917	42,513	818,629	47,401	885,023
V80	159	15	48,115	613,702	118,428	644,529	43,411	589,256	37,487	808,984
Average	153	12	17/20 (85%)				19/20 (95%)		19/20 (95%)	

## 5. Conclusions and Future Work

In this manuscript, we propose a benchmark based on the Signature Transform to evaluate visual summaries. For this purpose, we introduce a dataset consisting of videos obtained from Youtube related to science experiments with automatic audio transcriptions. A baseline, based on zero-shot text-conditioned object detection, is used as a preliminary technique in the study to evaluate the metrics. Subsequently, we present an accurate baseline built on the prior knowledge that the Signature provides. Furthermore, we conduct rigorous comparison against human-annotated summaries to demonstrate the high correlation between the measures and the human notion of a good summary.

One of the main contributions of this work is that techniques based on the Signature Transform can be integrated with any state-of-the-art method in the form of a gate that activates when the method performs worse than the metric,  $\text{std}(\text{RMSE}(\tilde{S}, \tilde{S}_*)) > \text{std}(\text{RMSE}(\tilde{S}, \tilde{S}))$ .

The experiments conducted in this work lead to the following conclusion: if a method for delivering a summarization technique is proposed that involves complex computation (e.g., DNN techniques or Foundation Models), it must provide better summarization capabilities than the baselines based on the Signature Transform, which serve as lower bounds for uniform random samples. If not, there is no need to use a more sophisticated technique that would involve greater computational and memory overhead and possibly require training data. The only exception to this would be when additional constraints are present in the problem, such as when summarization must be performed by leveraging audio transcriptions (as in the technique based on text-conditioned object detection) or any other type of multimodal data.

That being said, the methodology proposed based on the Signature Transform, although accurate and effective, is built on the overall representation of harmonic components of the signal. Videlicet, under certain circumstances, can provide summaries in which frames are selected due to low-level representations of the signal, such as color and image intensity, rather than the storyline. Moreover, it assumes that, in general, uniform random sampling can provide good summarization capabilities, which is supported by the literature. However, this assumption is not fulfilled in all circumstances. Therefore, in subsequent works, it would be desirable to develop techniques that perform exceptionally well according to the metrics while simultaneously bestowing a level of intelligence similar to the methodology based on Foundation Models. This would take into account factors such as the human concept of detected objects, leading to more context-aware and meaningful summarization.



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### Abbreviations

The following abbreviations are used in this manuscript:

DNN	Deep Neural Networks
AMT	Amazon Mechanical Turk
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
VLM	Visual Language Models
LLM	Large Language Models
GAN	Generative Adversarial Networks
CLIP	Contrastive Language–Image Pre-training
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
NLP	Natural Language Processing
CPU	Central Processing Unit
MOS	Mean Opinion Score

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