Digital Video Summarization Techniques: A Survey

Ashenafi Workie1
1MSc. Student
Adama Science and Technology University,
Department of Computer Science (CVR)

Rajesh Sharma2
2Assistant Professor
Adama Science and Technology University,
Department of Computer Science

Yun Koo Chung3
3Professor
Adama Science and Technology University,
Department of Computer Science

Abstract.- Video summarization which gives a short and precise representation of original video clips by showing the most representative synopsis is gaining more attention. The main objective of Video summarization is to provide a clear analysis of the video by removing redundant and extracting key frames contents from the video. The architecture in video summarization shows how a large video skims in to short and story contents. Many types of research were done in the past and ongoing until now. Therefore, multiple methods and techniques proposed by researchers from classical computer vision until the recent deep learning approaches. Most literature shows that most of the video generation and summarization approaches shift into deep generative models and variational auto encoders. These techniques may fall into summarized, unsupervised and deep reinforcement learning approaches. Video representation categorized in static and dynamic summarization ways. But video summarization still challenging with different problems, these are computational devices, complexity, and lack of dataset are some them. The effective implementation of video summarization applied in different real-world scenarios like movies tailor in the film industry, highlight in football soccer, anomaly detection video surveillance system.

Keywords: Video summarization, supervised, unsupervised, dynamic summarization;"
2. ARCHITECTURE IN VIDEO SUMMARIZATION

In the video summarization is a process that explains how large video content will summarize into short and concise information. The videos in small computation and storage resources regardless of losing an important section of the content. The mapping between the ground truth (original video) and the summarize one also important since. The following figure 1 shows the basic architecture of video summarization in line with the mapping function between the inputs (a large chunk of frame sequences) and summarizes (short and selected frame sequence).

![Figure 1](image1.png)

Figure 1 Learn video summarization from the whole contents by mapping F: V → S (right) linking two different domains V and S. [11].

![Figure 2](image2.png)

Figure 2 GAN based framework for video summarize using VAE variational auto encoder

3. VIDEO SUMMARIZATION

Multiple types of research done in video summarization potential methods and application areas in keyframe scenarios like a high-light football game. The proposed methods outlined by the researchers so far were both supervised and unsupervised approaches. But recently research the reinforcement learning mechanism also applied to it.

A. Supervised Methods

In a supervised learning approach video, summarization learns from labelled data by consisting of videos and along with ground-truth summary videos. Getting an annotated data is quite expensive, difficult and costly even in some way it becomes impossible [24] [11]. Due to its requirement of human-annotated video-summary pairs or per frame the training label is guided to summarize the video accordingly.

To address under the supervision of human-annotated video to produce a subset of contents. Selection problem. This annotation training sample along with the original source video that can teach how summarization will works while selecting informative subsets [14]. The target label annotation which is a user-created summaries that help by teachers for selecting the best video frames directed on how the algorithm to summarize in accordance with the guidance of user input fashion. Much work has been proposed to measure shot importance through supervised learning.

B. Unsupervised Methods

Unsupervised video summarization in Spatio-temporal feature and reduction with clustering methods. Unlike supervised methods without including annotated video summarize it is possible to create an unsupervised way. In Egocentric video summarization methods have also used unsupervised learning to categorize sports actions [12]. However, the video is challenging problems because of that placement of camera shows in a video a great variation in object vanishing points or angle, illumination conditions, and movement. The author used Alex Net which is a convolutional neural network to filter the key-frames (frames where camera wearer interacts closely with the
people) while finding a subset abstract story from whole contents.

C. Reinforcement Methods

based on the statistical probability of a given frame in a given video sequence. Use an end to end learning for training so needs high computational resources.

Reinforcement deep learning without a label or as an unsupervised video summarization approach works in the sequential process [28]. In this paper, the author used a deep summary network that can predict

![Training deep summarization network (DSN) via reinforcement learning. DSN receives a video Vi and takes actions [28].](image)

**Figure 3**

\[ R(S) = R_{div} + R_{rep} \]

Reward Function

| Videos |
| --- |
| CNN |
| LSTM |
| LSTM |
| LSTM |
| LSTM |
| BI-RNN |

\[ \text{summary } S = \{ v_{mi} | a_{mi} = 1, i = 1, 2, \ldots \} \]

actions \( A = \{ a_{ti} | a_{ti} \in \{0, 1\}, t = 1, \ldots, T \} \)

\[ \text{reward } R(S) \]

4. VIDEO REPRESENTATION

Video representation is an important problem in video pre-processing. A good video representation should include the key point and useful information for discrimination by discarding unnecessary information. Generally, in this video processing, video frames are usually represented as a matrix. In this paper author methods method, use the luminance information to keep the data in every single frame. In video summarization, mainly focus on creating a video summary that can finish watching within a short period of time. During this process, the generating mechanism for creating video frame contents may be static or dynamic approaches. The static video summarization is also known as R frame. Still, images consist of 3 types of classification. These are sampling, shot segmentation and scene-based classification where keyframes are extracted pre sampling in uniform as well as in a random manner. On the other hand, the dynamic video summarization during producing summarize informative video contents.

5. LITERATURE REVIEW

Taru et al., 2017 [31] propose a new method of video summarization into text. This approach takes an input of consumed video. The authors are motivated while the viewer of a video may not have time to go through full content. The aim of this research is a user can easily understand the summary in text format. Srinivas et al., 2016 [30] proposed an improved method for video summarization techniques. The aim is to get a summary content of a video which is interesting to the viewer and representing the whole video. The result is better while it compares with other methods.

Anomaly author, 2020 [29] proposed ILS-SUMM which an iterative local search for unsupervised video summarization. Its objective is to create automatically a short summary of the whole contents. Moreover, to indicate the high scalability of ILS-SUMM, the authors introduce a new dataset consisting of videos of various lengths. Zhou et al., 2018[28] develop a deep summarization network (DSN) to summarize videos for predicts each video frame probabilities. The training is an end to end reinforcement learning so the result is better than that of supervised approaches. SARMADI et al., 2017[27] proposed a general video summarization method that is divided into static and dynamic; Static Summary done through a keyframe.

Cai et al., 2018[24] proposed a generative modeling framework to learn representation with a variational autoencoder. Encoder-decoder attention for saliency estimation of raw video for generating the summary.

Song et al., 2015 [23] present TvSum an unsupervised summarization framework. Introduce a new benchmarks dataset. This approach produces superior quality summaries compare with other approaches. Yuan et al.,2017[22] present a novel Deep Side Semantic Embedding (DSSE) model to generate video summaries. In semantic relevance can be more effectively measured. Fu et al., 2019[4] proposed a GAN-based training framework through an unsupervised and supervised video summarization approach. The generator is focused on Ptr-Net that generates the cutting points of summarized fragments. Where “SumMe, TVSum, YouTube, and LoL datasets with remarkable improvements”. Rochan et al., 2019[11] present a method that learns to generate optimal video summaries. This r model goal is to learn a mapping function \( F: V \rightarrow S \).

Chu et al., 2015[8] developed a Maximal Biclique Finding (MBF) algorithm that is optimized to find sparsely co-occurring
patterns. The results suggest that summaries generated by visual co-occurrence tend to match more closely with human-generated summaries. Agyeman et al., 2019[7] present a deep learning approach to summarizing long soccer videos which are three-dimensional Convolutional Neural Network (3D-CNN) and Long Short-term Memory (LSTM) – Recurrent Neural Network (RNN). Fajtl et al., 2019[6] propose a novel method for supervised bi-directional recurrent networks such as BiLSTM combined with attention. Elfeki et al. 2019[4] conduct extensive experiments on the compiled dataset in addition to three other standard benchmarks. Vasudevan et al., 2017[3]

Introduce a new dataset, annotated with diversity and query-specific relevance labels. In the video, summarization can be a single-view or multiview. In single-view video Summarization proposed for summarizing a single-view using videos supervised approaches usually stood out with best performances. On the other hand, multi-view Video Summarization proposed a method that tends to rely on feature selection in using an unsupervised optimization paradigm.

| SN | Articles on topics | Objective | Methods |
|----|-------------------|-----------|---------|
| 1  | Single-view video Summarization [4] | ▪ summarizing single-view videos  
▪ Determinantal point processes (DPP) | ▪ RNN, LSTM, (Bi-LSTM) and DPP |
| 2  | Multiview video Summarization [4] | ▪ summarization methods tend to rely on feature selection  
▪ an unsupervised optimization paradigm  
▪ multi-view video summarization | ▪ Graph-based approach  
▪ 3D structure view axis |
| 3  | Supervised Methods Summarization [6] | ▪ A target label annotation which is a user-created | ▪ TVSUM, DPP SQDPP, and BiLSTM |
| 4  | Unsupervised Methods Summarization [23] | ▪ use hand-crafted heuristics to satisfy  
▪ Diversity, representativeness. | ILSUM, GAN, and VAE |
| 5  | Reinforcement approach | Reinforcement deep learning approach works in the sequential process | DSN |

6. GAN BASED VIDEO SUMMARIZATION
GAN-based training framework is a neural network that consists two adversarial Networks called generator and discriminator. This framework which combines the merits of unsupervised and supervised video summarization approaches [23]. The generator network is an attention-aware Ptr-Net that generates the cutting points of summarized fragments whereas the discriminator is a 3D CNN classifier to judge whether a fragment is from a ground-truth or a generated summarization. Therefore, GAN is a better one than that of others in different metrics.

![GAN-based training framework diagram](image)

Figure 4: An overview of our method. Present a GAN-based approach to video summarization.

7. CHALLENGES IN VIDEO SUMMARIZATION
In video summarization, the process is trivial in skimming important sections of the original content. The main challenge is the 1) training and preprocessing unbalanced training-test length. 2) complexity in application and development. 3) The temporal relationship between video frames in information like video tags, captions, comments and so on will need to be investigated in the future [22]. 4) inexpensiveness of training video mostly the annotated dataset.

8. APPLICATION OF VIDEO SUMMARIZATION
In video summarization, Keyframe extraction is an important part of many video applications, like video indexing, browsing, and video retrieval. Many professional and educational applications that involve generating or using large volumes of video and multimedia data are prime candidates for taking advantage of video content analysis techniques [33].
- movie trailer (film industry)
- Advert creation (Advertisement)
- football highlights (Recreation means)
9. CONCLUSION

This paper presents video summarization techniques, applications, and challenges. The architecture of video summarization focuses on a chunk of video summarize into short skim of potential information. Recently classical computer vision techniques for video summarization methods are dynamically shifting to deep learning especially deep generative model. Recurrent neural network, variational auto-encoders. Video summarization may handle in supervised (TVSUM, RNN and DPP SQDPP and BiLSTM), unsupervised (ILSUM, GAN and VAE) and even deep reinforcement learning approach (DSN).

GAN-based training framework as a powerful means of image and video generation. Video summarization is challenged different factor these ranges from dataset until computational device, especially in new deep learning models. The application video summarization can be used in a different scenario for different reasons these can be recreation, film industry, and security and reduce computation power. In general, a deep generative model and variational auto-encoder is a relatively good way of video summarization techniques in both static and dynamic summarization approaches.

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