Video Summarization through Total Variation, Deep Semi-supervised Autoencoder and Clustering Algorithms

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Abstract: Video summarization is an important tool considering the amount of data to analyze. Techniques in this area aim to yield synthetic and useful visual abstraction of the videos contents. Hence, in this paper we present a new summarization algorithm, based on image features, which is composed by the following steps: (i) Query video processing using cosine similarity metric and total variation smoothing to identify classes in the query sequence; (ii) With this result, build a labeled training set of frames; (iii) Generate the unlabeled training set composed by samples of the video database; (iv) Training a deep semi-supervised autoencoder; (v) Compute the K-means for each video separately, in the encoder space, with the number of clusters set as a percentage of the video size; (vi) Select key-frames in the K-means clusters to define the summaries. In this methodology, the query video is used to incorporate prior knowledge in the whole process through the obtained labeled data. The step (iii) aims to include unknown patterns useful for the summarization process. We evaluate the methodology using some videos from OPV video database. We compare the performance of our algorithm with the VSum. The results indicate that the pipeline was well succeed in the summarization presenting a F-score value superior to VSum.

1 INTRODUCTION

Daily, millions of videos are posted online, and some billions are available for public or private access, as on YouTube, for example. This content is provided by professionals or amateurs recorders, with many different devices as smartphones, surveillance or traffic cameras, among others. If we can provide some video summary, where the important information along the video is captured, it will greatly reduce the effort to browse through the enormous amount of content available, during a content based video retrieval task. Video summarization can be described as a subset selection problem, where the subsets contain frames, sparsely distributed in the whole sequence, or shots (set of temporally continuous interval-based segments). In both cases, the subset is smaller than the original video. The first case depends on key-frames selection. The second case is implemented through key shots selection.

In terms of pattern recognition tasks, two approaches are commonly applied to video summarization: unsupervised and supervised ones. The former uses heuristics to satisfy some properties in order to create summaries of the videos (Yuan et al., 2019; Li et al., 2019). Supervised methods (Zhao et al., 2019; Rochan et al., 2018) have access to raw videos and their corresponding ground truth summaries. Moreover, they use mainly the advances on deep learning to construct summaries. Although the supervised approaches have achieved better results than unsupervised techniques, labeling data with the defined ground-truth is not easily available.

A semi-supervised approach for fluid flow summarization, in the context of computational fluid dynamics, is proposed in (Ramos et al., 2018), but the authors did not present computational results. That work suggests to use transferring learning (Hu et al., 2016), combining labeled and unlabeled training sets in order to allow an autoenconder (AE) to efficiently learn how to encode samples in a reduced dimension space. After the AE training, the data set is processed by encoder and the feature vectors yielded enter into a clustering algorithm for classification. In this paper,

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we propose some improvements of this methodology and its application in video summarization.

Specifically, the methodology proposed in (Ramos et al., 2018) uses the following pipeline: (a) build the labeled training set $\mathbf{X}_s$ in the original space; (b) perform a coarse temporal flow segmentation using a simple similarity measure combined with an interval tree analysis; (c) select key numerical frames inside each obtained segment and assemble these frames in a training set $\mathbf{X}_t$; (d) a semi-supervised AE architecture is trained using the sets $\mathbf{X}_s$ and $\mathbf{X}_t$ to generate a metric distance (encoding function); (e) Apply X-means (Pelleg and Moore, 2000) clustering technique, with the metric distance, to compute the final partition of the frame sequence; (f) For each obtained cluster, take a key-frame to build the summarization sequence.

However, we have noticed that interval tree and a simple distance metric (like Frobenius distance) do not provide a satisfactory temporal segmentation in the frames of videos. Futhermore, the X-means algorithm tries to perform clustering without the need to set a pre-defined number K of groups. However, in the case of video sequences, the obtained results are not satisfactory. Besides, it is not clear the advantages of a high cost semi-supervised AE against a simpler unsupervised one. Therefore, in our work we propose to use total variation denoising, followed by differentiation and thresholding instead of the interval tree. We also replace the distance metric by a similarity measure based on the data correlation. Moreover, we perform clustering using K-means instead of X-means. We also compare a simple AE with the semi-supervised AE proposed in (Ramos et al., 2018) to evaluate the encoded quality of the former against the latter. Up to the best of our knowledge, this is the first work that applies a semi-supervised technique for video summarization in a systematic procedure. The whole methodology is the main contribution of this paper.

The remaining text is organized as follows. Section 2 we survey related works. In section 3 we describe the background techniques. The proposed methodology is presented in section 4. Next, section 5 discusses the computational experiments. Conclusions and possible future works are presented in section 6.

2 RELATED WORKS

A variety of video summarization techniques have been proposed as seen in the literature (Yuan et al., 2019; Zhao et al., 2019; Li et al., 2019; de Avila et al., 2011). In this paper we focus only on the technique based on image features to construct the summary. Generally, those techniques can be classified into unsupervised and supervised ones.

Clustering algorithms are one of the most popular unsupervised methodology. Given hand-craft features, similar frames are grouped forming a cluster and, from each cluster, the centers are taken to build the summary. Also, some works in unsupervised class use the frame histograms to learn clusters (de Avila et al., 2011). In (Mohan and Nair, 2018) there is an extension of this approach: the shot histograms are compressed by a high-level feature extractor before the clustering step. Other works construct models, as in (Lei et al., 2019), where the video is modeled as graph, where a graph vertex corresponds to a frame and the edge between vertexes is weighted by the Kullback-Leibler divergence of two frames based on semantic probability distributions. A clustering and a rank operation is applied on this graph method to create the summary. Recent works in unsupervised summarization have applied deep learning (Yuan et al., 2019; Zhao et al., 2019; Jung et al., 2018), using in general, convolutional or recurrent neural networks.

Deep learning is the principal tool in supervised summarization approaches. In this case, the summary is modeled as a classification problem, where in the ground truth, frames have labels that represent classes in the video (Jung et al., 2018). However, even with better results in video summarization, labeling for many video frames is tedious task that depends on the human intervention. Moreover, overfitting problems can frequently occur if no sufficient labeled data is available. Therefore a semi-supervised approach, which uses just one labeled video to summarize a set of other videos, can mitigate these limitations being a contribution to the area, which motivates our work.

3 TECHNICAL BACKGROUND

In mathematical terms, the total variation denoising computes a smooth version of an input signal $y \in \mathbb{R}^N$ by solving the optimization problem (Selesnick, 2012),

$$\hat{x} = \arg\min_{x \in \mathbb{R}^N} \frac{1}{2} \|y - x\|_2^2 + \lambda \|Dx\|, \quad (1)$$

where $x \in \mathbb{R}^N$; λ is the smooth factor, and D is a matrix $(N-1) \times N$ described in (Selesnick, 2012).

An AE can be viewed as a special case of feedforward neural network that is trained to reproduce its input at the output layer (Goodfellow et al., 2016). The AE architecture is depicted in Figure 1. Both encoder and decoder in this figure are implemented through a multilayer perceptron (MLP) neural networks where $W^{(\xi)}$ and $\mathbf{b}^{(\xi)}$ are the weight matrix and bias, respectively, for the layer ξ. Given an input V, the corresponding output $V^{(\xi)}$ at the ξ-th layer is computed as:

$$f^{(\xi)}(V) = V^{(\xi)} = \varphi\left(W^{(\xi)}V^{(\xi-1)} + \mathbf{b}^{(\xi)}\right), \quad (2)$$

where φ is a non-linear activation function (sigmoid function, for instance), which operates componentwisely.

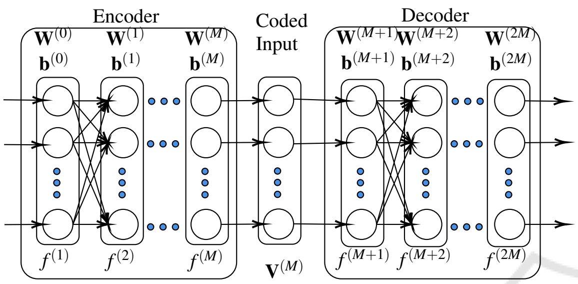


Figure 1: Autoencoder (AE) graph representation. Composed by one encoder and one decoder neural network. The sets of weights on each AE layer are represented in matrix form, where $W^{(m)}$ is the set of weights of the m-th layer. On the same way, the bias for the m-th layer in represented $\mathbf{b}^{(m)}$. Each $f^{(m)}$ represents the view of the layer as a transformation. For an input x, $f^{(M)}(x)$,$f^{(2M)}(x)$ are the encoder and decoder output respectively. The $V^{(M)} = f^{(M)}(\bullet)$ is the output of the encoder.

The semi-supervised AE used in this work has a loss function that incorporates the Fisher analysis, based on the terms S_c and S_b, that represent the intra-class variation and inter-class separation, respectively (Hu et al., 2016):

$$S_c^{(m)} = \frac{1}{Nk_1}\sum_{i=1}^{N_s}\sum_{j=1}^{N_s} P_{ij} d^2_{f^{(m)}}(\vec{x}_i, \vec{x}_j), \quad (3)$$

$$S_b^{(m)} = \frac{1}{Nk_2}\sum_{i=1}^{N_s}\sum_{j=1}^{N_s} Q_{ij} d^2_{f^{(m)}}(\vec{x}_i, \vec{x}_j), \quad (4)$$

where N_s is the number of samples of $\mathbf{X}_s$, $d^2_{f^{(m)}}$ is the square of the Euclidean distance, $P_{ij} = 1$ if $\vec{x}_j$ is one of k_1 nearest neighbors of $\vec{x}_i$, in the same class of it, and $P_{ij} = 0$ otherwise. Moreover, $Q_{ij} = 1$ if $\vec{x}_j$ is one of k_2 nearest neighbors of $\vec{x}_i$, belonging to a different class, and $Q_{ij} = 0$ otherwise.

In order to add a measure of the dispersion of training samples, it is introduced in the loss function the expression:

$$D_{ts}^{(m)}(\mathbf{X}_t, \mathbf{X}_s) = \left\| \frac{1}{N_t}\sum_{i=1}^{N_t} f^{(m)}(\vec{x}_{ti}) - \frac{1}{N_s}\sum_{i=1}^{N_s} f^{(m)}(\vec{x}_{si}) \right\|_2^2, \quad (5)$$

where N_s is the number of labeled samples and N_t the number of unlabeled elements.

Besides, it is necessary to add terms related to reconstruction errors, generating the final loss function used in (Hu et al., 2016), given by:

$$\begin{aligned}\min_{f^{(M)}, f^{(2M)}} J = & \alpha_c S_c^{(M)} - \alpha_b S_b^{(M)} + \beta D_{ts}^{(M)}(\mathbf{X}_t, \mathbf{X}_s) \\ & + \gamma \sum_{m=1}^{2M} (\|\vec{W}^{(m)}\|_F^2 + \|\vec{b}^{(m)}\|_2^2) \\ & + \frac{\theta_t}{N_t}\sum_{i=1}^{N_t} \|f^{(2M)}(\vec{x}_{ti}) - \vec{x}_{ti}\|_2^2 \\ & + \frac{\theta_s}{N_s}\sum_{i=1}^{N_s} \|f^{(2M)}(\vec{x}_{si}) - \vec{x}_{si}\|_2^2, \end{aligned} \quad (6)$$

where α_c, α_b, β, are parameters defining the importance of each corresponding term in the learning process, γ is a regularization parameter, and θ_s and θ_t controls the influence of the reconstruction errors in the objective function. The semi-supervised AE applied in this paper has an loss function given by expression (6) with $\alpha_c = 1$, $\alpha_b = 1$, $\beta = 0$.

For all AEs on this work, the training process uses backpropagation to efficiently calculate the gradient of expression (6) with respect to the parameters and a gradient descent method, in our work, based on adaptive moment estimation (ADAM) (Goodfellow et al., 2016).

4 PROPOSED METHOD

The video summarization approach proposed in this paper is based in transfer learning, whose main idea is to use the knowledge learned from a previous dataset, to learn about a new dataset. The authors propose the feature reduction, leaving data to a metric space using the semi-supervised AE with loss function (6). The summarization methodology follows the pipeline:

1. Query video processing using cosine similarity metric and total variation smoothing to identify classes in the query video frames;
2. With this result, user builds the labeled training set $\mathbf{X}_s$ of frames ;
3. Generate the unlabeled training set $\mathbf{X}_t$, that is composed by samples of the video database;
4. Training the AE with $\mathbf{X}_s \cup \mathbf{X}_t$, to learn the metric space;
5. Compute the K-means for each video separately, in the encoder space, with the number of clusters set as a percentage of the video size;

6. Select key-frames in the K-means clusters to define the summaries;

In this methodology, the query video is used to incorporate prior knowledge in the whole process through the obtained labeled data. The step (3) aims to include unknown patterns useful in the summarization process.

The utilization of cosine similarity metric in step (1) gives an efficient way to compare consecutive frames. Given q RGB frames $Q_0, Q_1, \cdots, Q_{q-1}$ with resolution $M \times N$, the first step is to convert these images to gray scale, generating the sequence $T_0, T_1, \cdots, T_{q-1}$. Then, to obtain the similarity $r(i)$ between the frames T_{i+1} and T_i, $i \in \{0, 1, \cdots, q-1\}$, we calculate:

$$r(i) = \sum_{m=1}^{M}\sum_{n=1}^{N}\left(T_{i+1}(m,n) - \bar{T}_{i+1}\right)\left(T_i(m,n) - \bar{T}_i\right) \times \left[\left(\sum_{m=1}^{M}\sum_{n=1}^{N}\left(T_{i+1}(m,n) - \bar{T}_{i+1}\right)^2\right) \times \left(\sum_{m=1}^{M}\sum_{n=1}^{N}\left(T_i(m,n) - \bar{T}_i\right)^2\right)\right]^{-1/2}, \quad (7)$$

where $\bar{T}_j = \frac{1}{M.N}\sum_{m=1}^{M}\sum_{n=1}^{N} T_i(m,n)$, $j \in \{i, i+1\}$. On the similarity formula, the terms in the square brackets is a normalization factor. Beside that, this formula is the cosine of the angle between the vectorized forms of matrices $(T_{i+1} - \bar{T}_{i+1})$and $(T_i - \bar{T}_i)$, which implies that $r(i) \in [-1, 1]$, $i \in \{0, 1, \cdots, q-1\}$.

On the pipeline, in steps (2)-(3), it is constructed a training set with two different subsets, one from frames whose labels are previously known and a second one whose labels are unknown. Using these sets the approach aims to improve the summarizing using transfer learning (Hu et al., 2016), transferring what is learned from the labeled set to the unlabeled group.

To build the labeled training set $\mathbf{X}_s$, we take a video query and applied total variation (expression (1)) in the similarity vector $S(q-1) = (r(1), r(2), ..., r(q-1)$, where r is calculated through expression (7). Next, we apply first order differential operation and with the absolute value of the difference, we use a threshold to determinate the segments of frames, which represent candidate clusters, or candidate labels in the video. This temporal segmentation by total variation combined with differentiation and threshold is validated, by a user, which defines the final frame classes. Then, the algorithm randomly selects a percentage of frames from each segment to construct the $\mathbf{X}_s$ set. This process is performed because we may have segments disjoint that contains the same visual information; for instance, a video clip containing a scene that periodically repeats along the time sequence. The proposed temporal segmentation pipeline is not able to distinguish such situation.

Next, in step (3), for each video of the database some frames are randomly selected to compose the unlabeled training set $\mathbf{X}_t$. After building the sets $\mathbf{X}_t$ and $\mathbf{X}_s$ they are used for training the semi-supervised AE of section 3. Considering each layer as a set of transformation of its correspondent input, the neural network learns a non-linear transformations set, transferring the knowledge from the labeled source domain to the target unlabeled domain. On this phases the aim is to learn the metric space, whose metric is $d_t^2(V^i, V^j) = \left\| f^{(M)}(V^i) - f^{(M)}(V^j) \right\|_2^2$, where $f^{(M)}(V^l)$ is the M-th layer output, the encoder output over the input V^l, as showed in Figure 1, also called the data in metric space by (Hu et al., 2016). In our case V^l is a vectorized version of the input frame T.

Following, with the metric space learned, given a frame sequence, it is coded by the encoder ($f^{(M)}$), transforming each frame from the sequence on vectors on the metric space. In sequence, a clustering algorithm is applied on these data using the metric learned. From each cluster generated by the K-means algorithm, the centroid nearest frame is chosen as the key-frame to build the video summarization, building a set of representative frames from the sequence. The number K of cluster to initialize K-means is set as a percentage of the video size. The corresponding fraction is determined having the number of classes in $\mathbf{X}_s$ as reference.

5 EXPERIMENTS

All the experiments were executed in a computer with Linux Ubuntu 18.04, 64 bits, 16 GB of RAM memory, 4 TB of hard-disk and Intel®i7 processor. The experiments were coded in Python, Tensorflow [1] and Keras using Tensorflow as background[2]

For the evaluation of our methodology, we use the F-score measure, comparing the video labels[3] with the labels from the clustering step. Moreover, due to the fact that the K-means implementation initializes the centroids in random way, we performed 30 realizations of the clustering and then take the mean F-score.

Besides, we want to compare the semi-supervised AE with the supervised one. Moreover, we need to analyze the efficiency of the encoder metric space

[1]The Python framework for Machine Learning coding.

[2]The Python framework for Deep Learning coding.

[3]All videos are labeled by a user.

against the original data space regarding the summarization. Consequently, we have three spaces for data representation: original, AE, and semi-supervised AE, named DTML AE, as performed in (Hu et al., 2016). Moreover, we compare our results with the VSum technique, published in (de Avila et al., 2011).

5.1 Dataset

To evaluate our methodology we use videos from Open Project Videos (OPV) dataset. This dataset was chosen because it is free available and commonly used to evaluate video summarization (Stavropoulos et al., 2019; Fajtl et al., 2018; Rochan and Wang, 2018; Rochan et al., 2018). We choose ten different videos from the dataset.

Each video sequence has between 503 and 3611 snapshots, in RGB format, each one with spatial resolution of 240×320. To save computational resources, we resize each image to 48×68 and converted it to gray scale.

5.2 Query Video Processing

Once a query video is selected, it is processed by our methodology. Hence, we compute the cross-correlation through expression (7), shown in Figure 2.(a). Next, the obtained result is processed with the total variation method (section 3), to obtain the smoother profile of Figure 2.(b). Then, the differentiation operator is applied with the result shown in Figure 2.(c). Following, a simple thresholding gives the result of Figure 2.(d) highlighting the intervals. In these operations, we use the following parameters values obtained by trial and error: (1) Total variation parameters: $\lambda = 0.2$ and number of iterations $N_{it} = 100$; (b) Threshold for differentiation operator result: $T = 0.3$.

The bars observed in Figure 2.(d) define the beginning and the end of each video segment, which are candidates to be classes in our approach. The user analyses these segments to identify the correct classes and performs the labeling of the query video images. Besides he/she selects a subset (in this case, 60% frames of each identified class) of labeled images to compose the set $\mathbf{X}_s$.

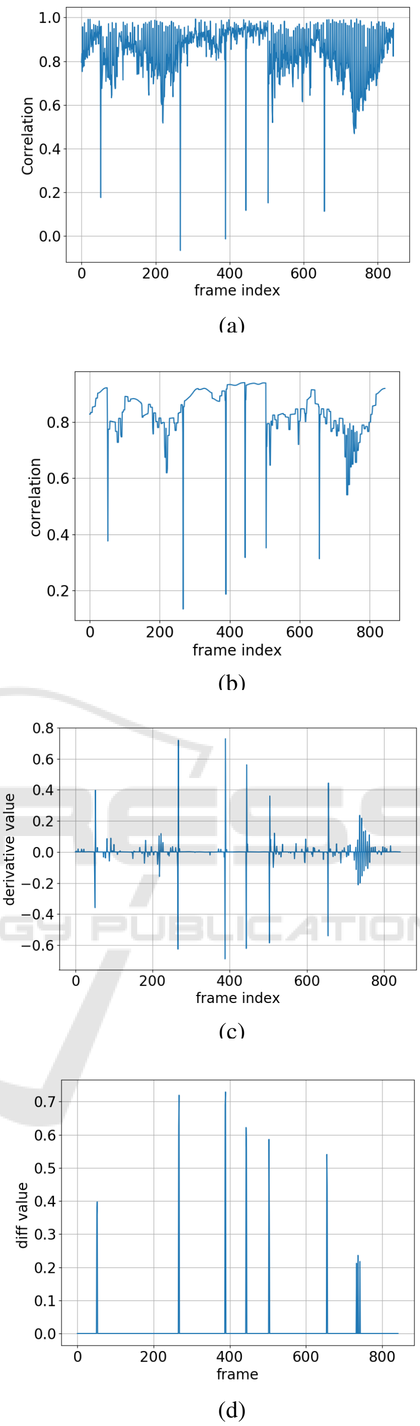


Figure 2: (a) Correlations $C_{i,i+1}$. (b) Total variation filtering signal $(T(C)_{i,i+1})$ obtained with $\lambda = 0.2$ and $N_{it} = 10$. (c) Visualization of the differentiation operation. (d) Intervals obtained by thresholding with $T = 0.3$ the differentiation result: $[1,53]$, $[54,267]$, $[268,389]$, $[390,445]$, $[446,505]$, $[506,656]$, and $[657,844]$.

5.3 Building Unlabeled, Training and Validation Sets

For each video of the database we randomly take 10% of samples and assemble these frames in the unlabeled set $\mathbf{X}_t$ and other 5% to construct a validation set. We then assemble the labels and unlabeled sets, $\mathbf{X}_s$ and $\mathbf{X}_t$, to form the training dataset.

5.4 Autoencoders

The autoencoders were build with the same configuration. The architecture had an input layer, five hidden layers and one output layer, in the sequence: $[3072, 1024, 800, 512, 800, 1024, 3072]$.

To implement the DTML AE we use Tensorflow and for the common AE the code was performed in Keras with Tensorflow as background. We did not implement both in Keras, because Tensorflow is more friendly to deal with the customized loss function of DTML AE approach (expression (6)).

For learning rate μ value in Tensorflow DTML AE, it was adopted $\mu = 0.001$ and for the common AE it was used the Keras default value.

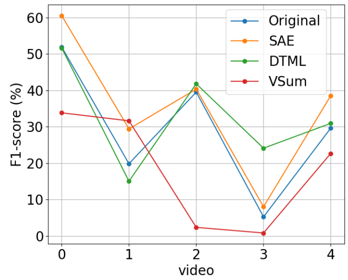
All parameters were chosen after some experiments, evaluating the reconstruction error evolution. The configuration above had have the least error in reconstruction in the evaluation. Furthermore, the number of epochs for training the network was equal to 500 to the common AE and 1000 for DTML AE.

5.5 Test 1

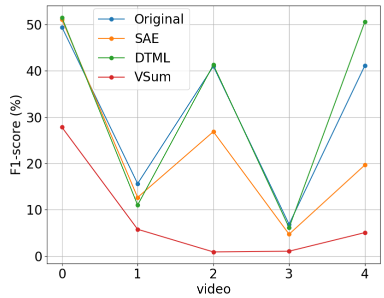
In this test we use five videos from the database for the final clustering step. This videos were similar to the query video used to make the $\mathbf{X}_s$ set. The keyframes were selected based in the proximity with the cluster centers.

The query video has seven segments, as pointed by total variation+diff+threshold (results in Figure 2) and checked in the ground truth. Hence, we set the number K of clusters to compute the K-means as $K \in \{5, 7, 8, 10\}$ in order to test the sensitivity of the F-score against this parameter. The results are shown in Figure 3.

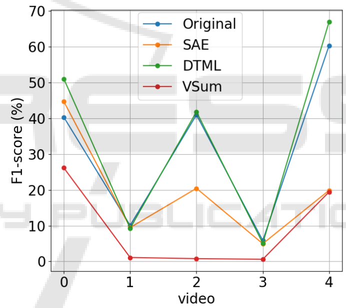
We can observe in Figure 3 the mean F-score for each video and for each space tested, as well as with different cluster numbers. From this figure we can observe that DTML AE approach had the higher percentile F-score in more videos than the others approaches. This result is confirmed by the mean percentile F-score of all videos as showed in Table 1.



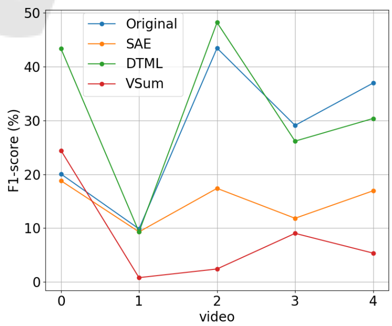
(a) clustering with k=5



(b) clustering with k=7



(c) clustering with k=8



(d) clustering with k=10

Figure 3: Mean F-score for the 30 realizations of k-means (a) Mean F-score for five test videos using $k = 5$ clusters; (b) Mean F-score for five videos using $k = 7$ clusters; (c) Mean F-score for five videos using $k = 8$ clusters (d) Mean F-score for five videos using $k = 10$ clusters.

Table 1: F-score for each space varying the clusters number, using the database with videos similar to the query.

	Mean F-score for space			
	original	common AE	DTML AE	VSum
k = 5	0.339	0.258	**0.340**	0.139
k = 7	0.308	0.230	**0.321**	0.081
k = 8	0.315	0.199	**0.348**	0.096
k=10	0.279	0.148	**0.315**	0.084

Table 2: F-score for each space varying the clusters number. Considering a database the entire videos.

	Space			
	original	common AE	DTML AE	VSum
k = 5	0.342	**0.376**	0.366	0.195
k = 7	0.338	0.258	**0.340**	0.139
k = 8	0.338	0.246	**0.348**	0.150
k=10	0.329	0.205	**0.334**	0.153

5.6 Test 2

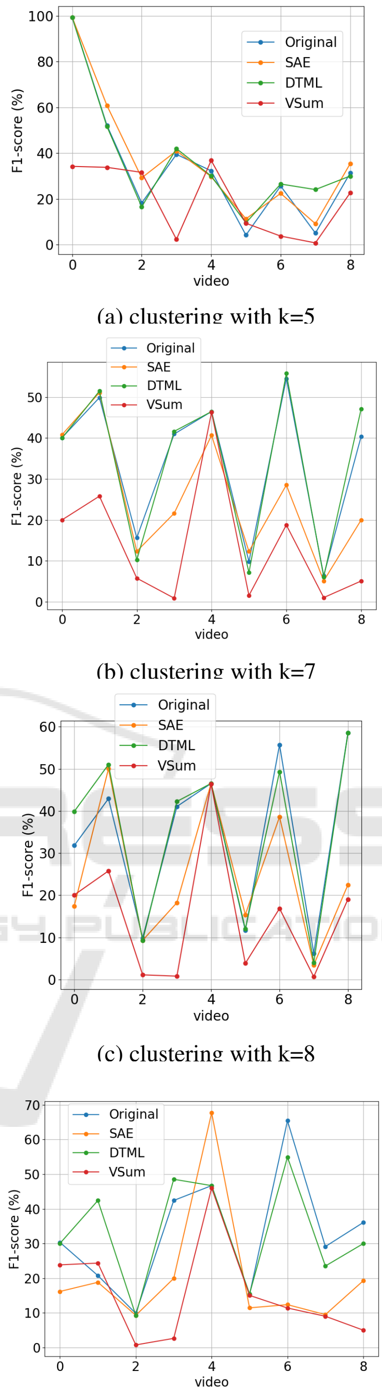
In this test we use all videos from the database for the final clustering step, in a total of 9 videos. This database includes videos with different patterns respect to the query video used to make the $\mathbf{X}_s$ set.

It was used the same procedure as the test before. The results are showed in Figure 4. By the results shown in Figure 4 we can observe again that DTML AE approach had the higher percentile F-score in more videos than the others approaches. This result is confirmed also by the mean percentile F-score of all videos reported in Table 2.

6 CONCLUSIONS

In this paper we propose a pipeline to video summarization based on a semi-supervised approach, where an autoenconder is used to learn a metric space and the summarization is performed in the encoder space.

The methodology is inspired in the work (Ramos et al., 2018), originally proposed for fluid summarization in numerical simulations without computational experiments reported. We have adapted the methodology for video summarization, replacing some elements of the original pipeline to total variation (TV) with differentiation and thresholding; cosine similarity; the k-means for clustering. Also, we perform tests using simple AE, the DTML AE proposed in (Hu et al., 2016), and compare the methodology results with the VSum technique.



(a) clustering with k=5

(b) clustering with k=7

(c) clustering with k=8

(d) clustering with k=10

Figure 4: Mean F-score for the 30 realizations of k-means (a) Mean F-score for five videos using $k = 5$ clusters; (b) Mean F-score (%) for five videos using $k = 7$ clusters; (c) Mean F-score for five videos using $k = 8$ clusters (d) Mean F-score for five videos using $k = 10$ clusters.

The results showed that the F-score for DTML AE gives the best result in mean, when compared with a common AE, the original data space, and VSum methodology. This result is the same when we consider videos that are similar to the query video, or when we include videos with low similarity with the query.

As future works we intent to improve the pipeline by testing the methodology with convolutional autoencoders, using larger datasets for tests and also to apply a more state of art transformation, as perceptual hashing (Monga and Evans, 2006). Moreover, we want to explore the methodology to content visual retrieval and to compare the results with more recent approaches of videos summarization.

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