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Abstract

In this paper, we propose a novel fully unsupervised framework that learns action representations suitable for the action segmentation task from the single input video itself, without requiring any training data. Our method is a deep metric learning approach rooted in a shallow network with a triplet loss operating on similarity distributions and a novel triplet selection strategy that effectively models temporal and semantic priors to discover actions in the new representational space. Under these circumstances, we successfully recover temporal boundaries in the learned action representations with higher quality compared with existing unsupervised approaches. The proposed method is evaluated on two widely used benchmark datasets for the action segmentation task and it achieves competitive performance by applying a generic clustering algorithm on the learned representations.¹

1. Introduction

Unconstrained videos capturing real-world scenarios are usually long, untrimmed and contain a variety of actions which can be effortlessly divided by a human observer into semantically homogeneous units. The task of action segmentation, which we target in this work, is the process of identifying the boundaries of an action, i.e. *pour water*, in an untrimmed video of an activity, i.e. *making tea*, even when temporally adjacent actions may have very small visual variance between them. This process is a key step in understanding and contextualizing the video. It is also crucial for video browsing, indexing, and summarisation and has applications in areas such as surveillance systems, action recognition, video content-based retrieval, assistive technologies, and robot-human interactions.

This problem has been traditionally tackled through supervised learning approaches [8, 12, 16, 17, 20, 32]. Such approaches require a large amount of annotated training data and typically suffer from domain adaptation problems, being unable to generalize to large-scale target domains.

¹Code will be released in a GitHub repository upon acceptance.

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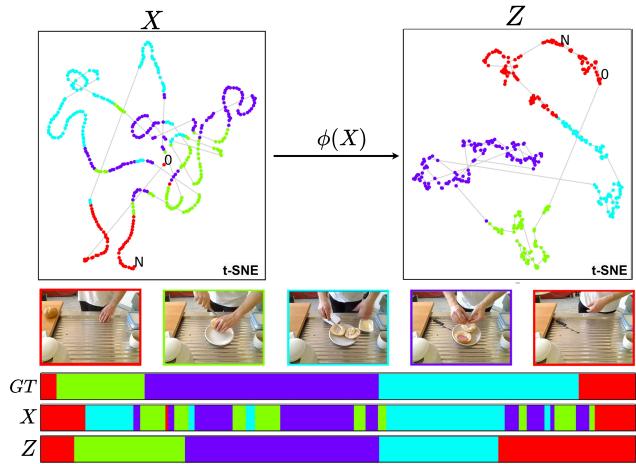


Figure 1. Our approach learns a parametrized function ϕ that transforms the input feature space (X) into a new one (Z), where actions, visualized through different colours, can be easily unveiled by a generic clustering algorithm. The continuous line connects points representing frames from time 0 to N in a t-SNE projection. GT stands for ground truth.

More recently, weakly-supervised and semi-supervised approaches have shown to be an effective way to learn video representations convenient for action segmentation without requiring or requiring very little manual annotations [2, 6, 9, 10, 13, 18, 21–24, 28]. However, these approaches are still data-hungry and computationally expensive. Unsupervised approaches have developed following two different research lines [1, 15, 19]. Most of them focus on grouping actions across videos and rely on the use of activity labels [14, 15, 19, 27, 29, 31], therefore putting more emphasis on the quality of the representation. A few of them, the most computationally efficient, act on a single video to recover clusters [25] or detect temporal boundaries [7] and do not require any manual annotation.

Our approach stands between these two research lines. We assume that the atomic actions can effectively be modelled as clusters in an underlying representational space and we propose a novel framework that maps the initial feature space of a video into a new one, where the temporal-semantic clusters corresponding to atomic actions are unveiled. Similarly to other unsupervised approaches that rely on similar assumptions [14], our focus is on representation

108 learning. However, similarly to [7, 25], our method takes
109 as input a single video and doesn't care whether the same
110 action is present in similar videos or not. This has con-
111 siderable practical advantages for downstream applications
112 since it can be in principle applied to any video no matter
113 the dataset it belongs to nor if there exist videos having a
114 similar temporal structure. Action segmentation is obtained
115 by applying a generic clustering algorithm on the learned
116 temporal-semantic aware (TSA) representations (see Figure
117 1). Our contributions are as follows:
118

- We introduce the novel approach to action representation learning that uses a shallow network and the single video itself as input, without the need for additional training data.
- We demonstrate the effectiveness of using a triplet loss operating on similarity distributions with a novel triplet selection strategy based on a downsampled temporal-semantic similarity weighting matrix for the task of action segmentation.
- We detail ablation study and we achieve state-of-the-art metrics on the *Breakfast* and *Youtube INRIA Instructional* benchmark datasets without using any training data than a single video itself as input.

2. Related work

134 **Fully supervised approaches.** Action Segmentation has
135 been traditionally tackled as a supervised learning prob-
136 lem. Existing approaches belonging to this category differ
137 mainly in the way temporal information is taken into ac-
138 count by the model. Traditional approaches follow a two-
139 step pipeline, that first generates frame-wise probabilities
140 and then feeds them to high-level temporal models as in
141 the Hidden Markov Model Tool Kit (HTK) approach [12]
142 or in [32], which is based on recurrent neural networks.
143 Lately, there has been a proliferation of models based on
144 temporal convolutions to directly classify the video frames.
145 Encoder-Decoder Temporal Convolutional Networks (ED-
146 TCNs) [16] use a hierarchy of temporal convolutions to
147 perform fine-grained action segmentation, but they can act
148 solely on low-temporal resolution videos. Instead, Multi-
149 Stage Temporal Convolutional Network (MS-TCN and its
150 improved version MS-TCN++) can act on the full tempo-
151 ral resolution of the videos and achieves increased per-
152 formance [8, 20]. Spatio-temporal convolutional layers [17]
153 have shown promising results in capturing temporal depen-
154 dencies while being easier to train than previous methods.
155

156 The main drawback of traditional supervised approaches
157 to action segmentation is the requirement of a large amount
158 of quality labelled data for training, which limits their ap-
159 plicability to large-scale domains outside of existing pre-
160 segmented datasets [12, 20].

162 **Weakly and semi-supervised approaches.** To alleviate the
163 need for large annotated datasets, weakly supervised tech-
164 niques for video segmentation involve using transcripts (or-
165 dered list of the actions occurring in the video), visual simi-
166 larities, and audio information to generate pseudo-labels for
167 training [9]. In [13], a Gaussian Mixture Models + Convo-
168 lutional Neural Networks (GMM+CNN) is first initialized
169 and used to infer the segments of a video given a transcrip-
170 tion of it. The new segmentation is used to re-estimate and
171 update the model parameters until convergence. In [23],
172 a recurrent neural network is used to model a discrimina-
173 tive representation of subactions, and a coarse probabilis-
174 tic model to allow for temporal alignment and inference
175 over long sequences. Some approaches use machine learn-
176 ing models to infer the segments of the video [21]. Other
177 approaches, such as those based on frame-to-frame visual
178 similarities [10], self-attentions mechanism [22] or iter-
179 ative soft boundary assignment [6], enforce consistency be-
180 tween the video and labels without the need for temporal
181 supervision. In the work [9], a network is trained on long
182 videos which are only annotated by the set of present ac-
183 tions and are trained by dividing the videos into temporal
184 regions that contain only one action class and are consis-
185 tent with the set of annotated actions. The work in [24]
186 adopts a Hidden Markov Model grounded on a Gated Re-
187 current Unit (GRU) for labelling video frames. This model
188 has been subsequently improved in [18], where the model is
189 trained through a Constrained Discriminative Forward Loss
190 (CDFL) that accounts for all candidate segmentations of a
191 training video, instead than a single one. [2] uses speech
192 as additional sources of human-generated information in a
193 weakly-supervised framework.

194 Recent work has proposed a semi-supervised approach
195 [28] (ICC) consisting of a previous unsupervised training
196 with a contrastive loss followed by a supervised training
197 step with a small amount of labelled samples. These meth-
198 ods are limited to videos with transcripts and cannot be gen-
199 eralized to unconstrained videos.

200 **Unsupervised learning approaches.** Unsupervised learn-
201 ing approaches typically learn action representation in a
202 self-supervised fashion and then apply a clustering algo-
203 rithm to obtain the action segmentation (assuming that the
204 number of clusters is known). Some methods model that
205 minimizes prediction errors exploiting the order of scripted
206 activities [14] or combining temporal embedding with vi-
207 sual encoder-decoder pipelines [29]. Other approaches use
208 deep learning architectures, including an ensemble of au-
209 toencoders, and classification networks that exploit the re-
210 lation between actions and activities [19]. Based on the as-
211 sumption that in task-oriented videos actions occur in a sim-
212 ilar temporal space, [14, 27] learn a strong temporal regu-
213 larization that partially hides visual similarity. [31] propose
214 a Self-Supervised Co-occurrence Action Parsing method

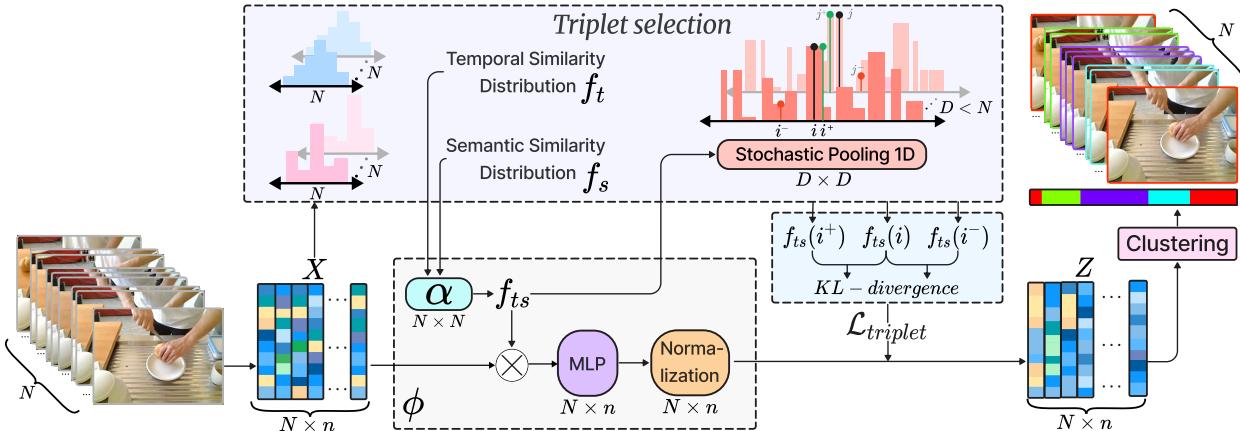


Figure 2. Overview of the proposed TSA framework illustrated on a sample video of the Breakfast Dataset: network architecture transforming the initial features X into the learned features Z through a shallow network with a novel triplet selection strategy and a triplet loss based on similarity distributions.

(SSCAP), for unsupervised temporal action segmentation which takes the recurrence of sub-actions into account in estimating the temporal path, and hence is able to handle complex structures of activities. Recently, [15] proposed a joint self-supervised representation learning and online clustering approach, which uses video frame clustering as a pretext task and hence directly optimizes for unsupervised activity segmentation (TOT+TCL).

Even if these approaches do not require labelled data, they are data-hungry and are not suitable for transferring the learned knowledge to a dataset with a different distribution and they demonstrated modest performance for the task of action segmentation at the video level. In contrast, we aim at unveiling the clusters underlying a single video. There is limited work in the literature on learning action representations in a self-supervised manner within a single video. [1] proposes a model based on an encoder LSTM architecture with Adaptive Learning (LSTM+AL) that minimizes the prediction error of future frames and assigns segmentation boundaries based on the prediction error of the next frame. Some recent works proposed to learn event representations [3,4] and the underlying graph structure from a single sequence (DGE) [5], where temporal windows are taken into account instead of all frames.. In both cases, these approaches were not tested for the action segmentation of complex activity videos (high-temporal resolution), but only on low-temporal resolution image sequences.

Fully unsupervised approaches. Clustering methods, which generate a partition of the input data based on a specific similarity metric, have been poorly investigated within the field of action segmentation. However, very recent work [25] has shown that simple clustering approaches, i.e. K -means, are instead a strong baseline for action segmentation. They hence proposed a new clustering approach called Temporally-Weighted FINCH (TW-FINCH), which is similar in spirit to the clustering approach named FINCH [26]

but takes into account temporal proximity in addition to semantic similarity. Recently, [7] proposed to detect action boundaries (ABD) by measuring the similarity between adjacent frames based on the insight that actions have internal consistency within and external discrepancy across actions. We based our approach on the same insight that we modelled via a deep metric learning approach.

3. Methodology

We assume that the representational clustering grounding action segmentation encodes both temporal and semantic similarity, based on two observations: (i) an action in a video is a sequence of images temporally continuous, therefore temporal adjacent frames are likely to belong to the same action. (ii) frames corresponding to the same action (but not necessarily temporal adjacent) should have similar representation, encoding the common underlying semantic.

Formally, let $X \in \mathbb{R}^{N \times n}$ denote the matrix of n -dimensional feature vectors for a given sequence of N frames. We aim at learning a parametric function ϕ such that given the input feature matrix X , new Temporal-Semantic Aware (TSA) (see Figure 2) representations $Z \in \mathbb{R}^{N \times n}$ are obtained as $Z = \phi(X)$.

3.1. Triplet loss and triplet selection

To learn ϕ , we minimize a triplet loss function (defined in Equation 1) that implements an original approach to select the triplets appropriately by relying on temporal-semantic similarity distributions f_{ts} obtained as the weighted sum of the temporal and the semantic similarity distributions, say f_t and f_s , $f_{ts} = \alpha \cdot f_t + (1 - \alpha) \cdot f_s$, where $\alpha \in [0, 1]^{N \times 1}$ a vector of learning parameters of the function ϕ . Under the model assumptions, it is easy to see that the similarity of $f_{ts}(k)$ and $f_{ts}(k')$ will be large when k and k' belong to the same event, and it will be small when k and k' belong to two different events.

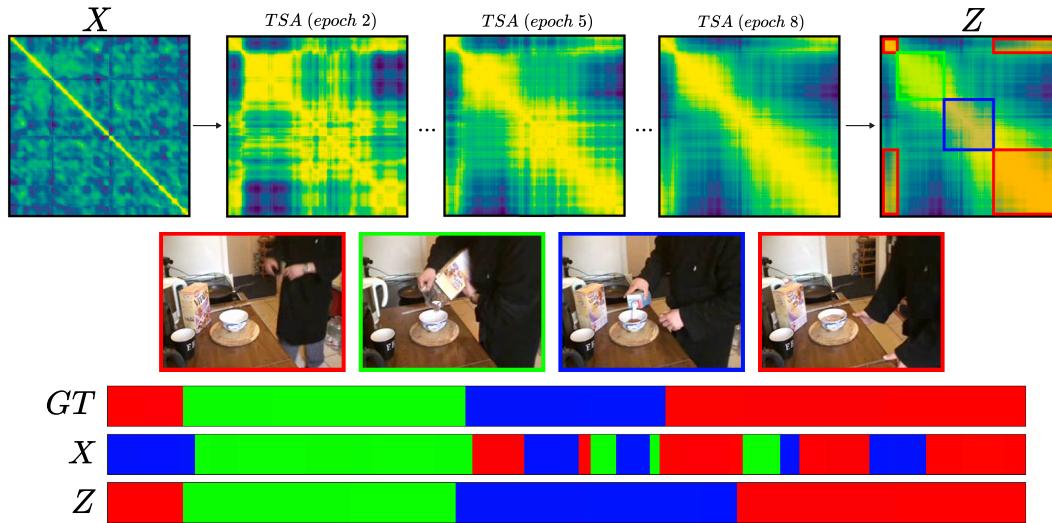


Figure 3. Example of training and result obtained by using the TSA approach for a sample video of the *Breakfast Action Dataset* (P34.cereals). **(a)** Cosine similarity affinity matrix for initial features X and evolution of the learned features Z for different training epochs. Actions are highlighted as neighbour communities referring to the segmentation of the video when a clustering algorithm is applied. **(b)** Segmentation plots showing the ground truth, and the result of applying the same clustering algorithm to initial features X (IDT) and to the learned features Z (TSA).

Semantic similarity distribution: To define f_S , we assume that the set of most similar frames in the original feature space of an anchor i is very likely to be part of the same action. The similarity of an anchor i to all other frames is defined element-wise via a pairwise similarity, upon normalization to the total unit weight, $f_S = w_{ij}/W$, with $W = \sum_{i,j} w_{ij}$ and $w_{ij} = \exp(-(1 - d(x_i, x_j))/h)$, and where E is the set of pairwise relations, $d(\cdot, \cdot)$ is the cosine distance and h is the filtering parameter of the exponential function. The resulting pairwise similarities are normalized to represent empirical joint probability distributions between pairs of elements in the sequence.

Temporal similarity distribution: To define f_t , we assume that as we move away from the anchor i , the likelihood of a feature vector $x_{j \neq i}$ to represent the same action as frame i decreases. To model this behaviour, we define a weight function $w(\cdot)$ that depends on the temporal frame distance d from the given frame as $w(d) = -1 + 2\exp(-\frac{1}{\beta}d)$ where β is a constant that controls the slope of the weight function and d is the temporal distance between frames. By imposing that $w(L/2) = 0$, and then solving for β , we get that the constant β can be expressed in terms of the positive window length, that is: $\beta = -L/(2\ln(\frac{1}{2}))$. The temporal and semantic distributions are downsampled to reduce computational costs using stochastic pooling during the training. An anchor index $i \in D$. Its set of positive samples \mathcal{P}_i is taken as the 5% of the frames with the highest similarity values in i -row of the

temporal-semantic affinity matrix f_{ts} . We define the negative set \mathcal{N}_i as the frames whose i -row f_{ts} is between the mean and the sum of the mean and standard deviation of the similarity metric. Our triplet loss is defined as:

$$\mathcal{L}_{triplet} = \frac{1}{D} \sum_{i \in D} \max(0, KL(f_{ts}(i) || f_{ts}(i^-)) - KL(f_{ts}(i) || f_{ts}(i^+))) \quad (1)$$

where KL represent the KL-divergence of the temporal-semantic similarity distribution f_{ts} . For each loss term, given an anchor index $i \in D$ with $D < N$, we define the triplet $\{i, i^+, i^-\}$ where $i^+ \in \mathcal{P}_i$ and $i^- \in \mathcal{N}_i$ that they are the sets of positive and negative indices, respectively.

Using probability distribution functions (PDFs), f_{ts} as feature vectors, instead of initial features X can provide several benefits for action segmentation. Since PDFs consider all the information in the video for each frame, they are smoother and more robust compared to the initial features extracted from the data X (they can be noisy or contain irrelevant information). In the ablation study (see Section 4.3), we will prove that this can improve the accuracy and robustness of the triplet loss for action segmentation.

4. Experimental evaluation

4.1. Experimental setup

Datasets: We report results on two widely used temporal action segmentation datasets: (1) the *Breakfast Action Dataset* [11] consists of 10 activities related to breakfast

432 preparation, performed by 52 different individuals in 18 different kitchens for a total of 1712 individual videos of 64 dimensions each feature vector; (2) the *Youtube INRIA Instructional Dataset* [2] consists on 150 instructional videos from YouTube whose feature vectors are 3000-dimensional. These include 5 different unrelated activities (changing tire, preparing coffee, performing a Cardio Pulmonary Resuscitation, jumping a car and repotting a plant), lasting 2 minutes on average. The most challenging part of this dataset is the amount of background frames present in each video, which reaches up to 63.5% of the frames in the dataset.

444
445 **Evaluation metrics:** We use a clustering algorithm on the learned representations to segment the video into its atomic actions. To match the predicted segmentation labels and the ground truth, we follow the Hungarian matching algorithm to obtain a one-to-one mapping between the predicted labels (cluster index) and the ground truth at video-level. Following previous work [1, 7, 25, 27], we report three widely used metrics: (i) accuracy of the segmentation and action identification, computed as the *Mean over Frames* (*MoF*) metric, which indicates the percentage of action predicted frames correctly labelled after the Hungarian matching. (ii) Similarity and diversity of the predicted segments, calculated as the *Intersection over Union* (*IoU*) metric, also known as the Jaccard Index or Jaccard similarity coefficient. (iii) The *F1-score* computed across the predicted segments and the known ground truth to evaluate the quality of the action segmentation. Note that, among unsupervised methods, [14, 27] look for a one-to-one global matching (shared across all videos of a given task) instead that at the video-level. This generally leads to poorer performance than computing the the Hungarian at video-level.

4.2. Implementation details

466 **Input features.** To ensure a fair comparison to state-of-the-art methods targeting the action segmentation task, we 467 use the same datasets and input features for the frame-level 468 initial representations as in [1, 7, 14, 25, 27, 29]. For the 469 *Breakfast Action* we use the Improved Dense-Trajectory 470 (IDT) [30] features. These were provided by the 471 authors of CTE [14] in their open-sourced implementation. 472 For *Youtube Inria Instructional* we use a set of frame-level 473 representations given by their original authors, which are 474 features vectors formed by a concatenation of HOF descriptors 475 and features extracted from VGG16-conv5 network.

476 **Model architecture** We used a shallow neural network 477 consisting in our case of a multi-layer perceptron with a 478 single hidden layer followed by a ReLu activation function. 479 This makes our approach (Figura 2) easy to train and more 480 suited for practical applications than existing approaches 481 consisting of multiple convolutional layers and/or recurrent 482

483 networks. Empirical experiments showed that using a single 484 hidden layer was easier and faster to train than deeper 485 models while achieving similar performance. The reported 486 results are also invariant to the number of units in the hidden 487 layer.

488 **Model training.** The parameter L used in this paper is 489 the average number of action classes for a specific dataset, 490 6 and 9 for BF and YII, respectively. Empirical experiments 491 showed that using a single hidden layer was easier and faster 492 to train than deeper models while achieving similar performance. 493 The reported results are also invariant to the number 494 of units in the hidden layer. The architecture used to obtain 495 our features is a multi-layer perceptron with as many units 496 as the input feature dimensionality, n , although this could 497 be changed to obtain the desired output dimensionality. The 498 batch size is equivalent to the downsampling and the number 499 of batches will be the quotient of the number of frames 500 and the batch size. We define the distance hyperparameter 501 as the minimum threshold ε that the difference of the last 502 two losses should take. This hyperparameter is set to track 503 early stops with a patience of 2 times. The minimum and 504 maximum training epochs are fixed at 2 and 50, respectively. 505 The initial learning rate depends on each dataset and follows 506 an exponential learning decay rate of 0.3 and a weight decay 507 L_2 of 10^{-3} as the regularisation parameter.

4.3. Model study

514 Figure 3 illustrates how the initial features are modified 515 during training to gradually unveil the representational clusters. 516 On the left, we visualize the affinity matrix computed 517 from the feature matrix on the original feature space. In the 518 middle, we visualize the affinity matrix computed at 519 different epochs during training and finally, on the right, our 520 learned representations at the end of the training. Finally, 521 the clusters, that were completely hidden on the initial affinity 522 matrix, become more and more visible along the diagonal. 523 The same label appears at different time intervals in the 524 off-diagonal clusters, as reflected by the ground truth.

525 **Ablation study.** In Table 2, we show the importance of 526 modelling both temporal and semantic similarities, by using 527 both f_t and f_s (being f_{ts} when both are marked). In 528 Table 3, we can see that by representing a frame through a 529 PDF instead of a simpler feature vector, we can significantly 530 improve the accuracy of action segmentation. Without this 531 representation, the approach may not accurately capture the 532 similarity between points in X , leading to segmentation 533 errors. In addition, the average calculation time tells us that 534 this improvement is achieved with no additional cost.

Breakfast Action Dataset					
Baselines		MoF	IoU	F1	T
Equal Split*		34.8	21.9	-	X
Spectral*		55.5	44.6	-	X
Kmeans*		42.7	23.5	-	X
FINCH* [26]		51.9	28.3	-	X
Unsupervised					
LSTM+AL [1]		42.9	46.9	-	✓
VTE [29]		52.2	-	-	✓
DGE* [5] (Kmeans)		58.8	47.8	51.6	X
DGE* [5] (Spectral)		59.5	48.5	51.7	X
TW-FINCH [25]		62.7	42.3	49.8	X
ABD [7]		<u>64.0</u>	-	52.3	X
Ours* (Kmeans)		63.7	53.3	57.9	X
Ours* (Spectral)		63.2	<u>52.7</u>	<u>57.8</u>	X
Ours* (FINCH)		65.1	52.1	54.6	X

Table 1. Action Segmentation results on the BF and YII dataset by applying the Hungarian matching at the video-level. T denotes whether the method has a training stage on target activity/videos. The dash indicates “not reported”. * denotes results computed by ourselves. The best and second-best results are marked in bold and underlined, respectively.

f_t	f_s	BF (kmeans)		BF (FINCH)		YII (kmeans)		YII (FINCH)	
		F1	MoF	F1	MoF	F1	MoF	F1	MoF
X	✓	38.6	44.4	35.3	49.0	46.8	52.8	44.1	53.7
✓	X	57.7	63.5	54.0	64.6	54.8	59.4	53.5	62.2
✓	✓	58.0	63.7	54.6	65.0	55.3	59.7	54.7	62.4

Table 2. Ablation studies the BF and YII datasets, showing the importance of modelling both temporal and semantic information.

4.4. Experimental results

To obtain the final segmentation from the learned action representations we apply three different clustering algorithms: K-means, Spectral clustering and FINCH [26]. For comparison purposes, we report here the results of existing unsupervised methods that were computed by the proposing authors by applying the Hungarian matching at the video-level. We used the code made publicly available by the authors ² to compute the performance of DGE on the considered datasets, since this approach, similar to ours, computes a video representation suitable for the task of temporal/action segmentation.

Breakfast Action: The left-hand table 1 reports the resulting metrics for the BF dataset, obtained with a learning rate 0.051, distance 0.032 and batch size 128. Our method significantly outperforms all other existing approaches. Special attention on F1, which is considerably better in our results, which tells us better quality and less over-segmentation in our method. These results are consistent with all three clustering approaches considered for obtaining the final segmentation of our learned features. We can therefore conclude that TSA outperforms SoTA approaches for the downstream task of action segmentation. Examples of segmentation results on a few videos for this dataset can be seen in Figure 3 (b) and Figures 4 (a)-(c).

²<https://github.com/mdimiccoli/DGE>

Youtube INRIA Instructional Dataset			
Baselines		F1	MoF
Equal Split*		27.8	30.2
Spectral*		44.6	55.1
K-means*		29.4	38.5
FINCH* [26]		35.4	44.8
Unsupervised			
LSTM+AL [1]		39.7	-
DGE* [5] (Kmeans)		47.0	42.1
DGE* [5] (Spectral)		48.9	44.8
TW-FINCH [25]		48.2	56.7
ABD [7]		49.2	67.2
Ours* (Kmeans)		55.3	59.7
Ours* (FINCH)		54.7	62.4

Table 3. Comparative results obtained by using the triplet loss with and without a PDF of similarities, and the average running time for a video in the BF (left) and YII (right) datasets.

Youtube INRIA Instructional: The right-hand table 1 reports the resulting metrics for the YII dataset, obtained with a learning rate 0.403, distance 0.892 and batch size 12. This dataset is particularly challenging because of the nature of the annotations, where most of the frames in each video are labelled as background frames. To enable direct comparison, we follow the same procedure used in previous work [7, 25, 27] and report results by removing the ratio ($\tau = 75\%$) of the background frames from the video sequence and then report the performance. To capture the temporal dependencies in the time window, we compute the temporal similarity matrix before subtracting a ratio of the background frames. Our method improves the best *F1* metrics from the literature with a large margin, which indicates the quality of the segmentation in our method on both datasets, as the MoF does not reflect the quality, especially when the whole sequence is dominated by some very long segments. A segmentation output sample of our method for this dataset is plotted in Figures 4 (d)-(f). Also for this dataset, our results are consistent with all two clustering approaches.

It is important to highlight the cases in Figures 4 (a), (b) and (d) where the effectiveness of our approach can be clearly observed. In these examples, the MoF values are comparable in both clustering methods, with the TW-FINCH method exhibiting slightly higher MoF values. However, it is noteworthy that our *F1* is significantly better which shows a better quality of segmentation.

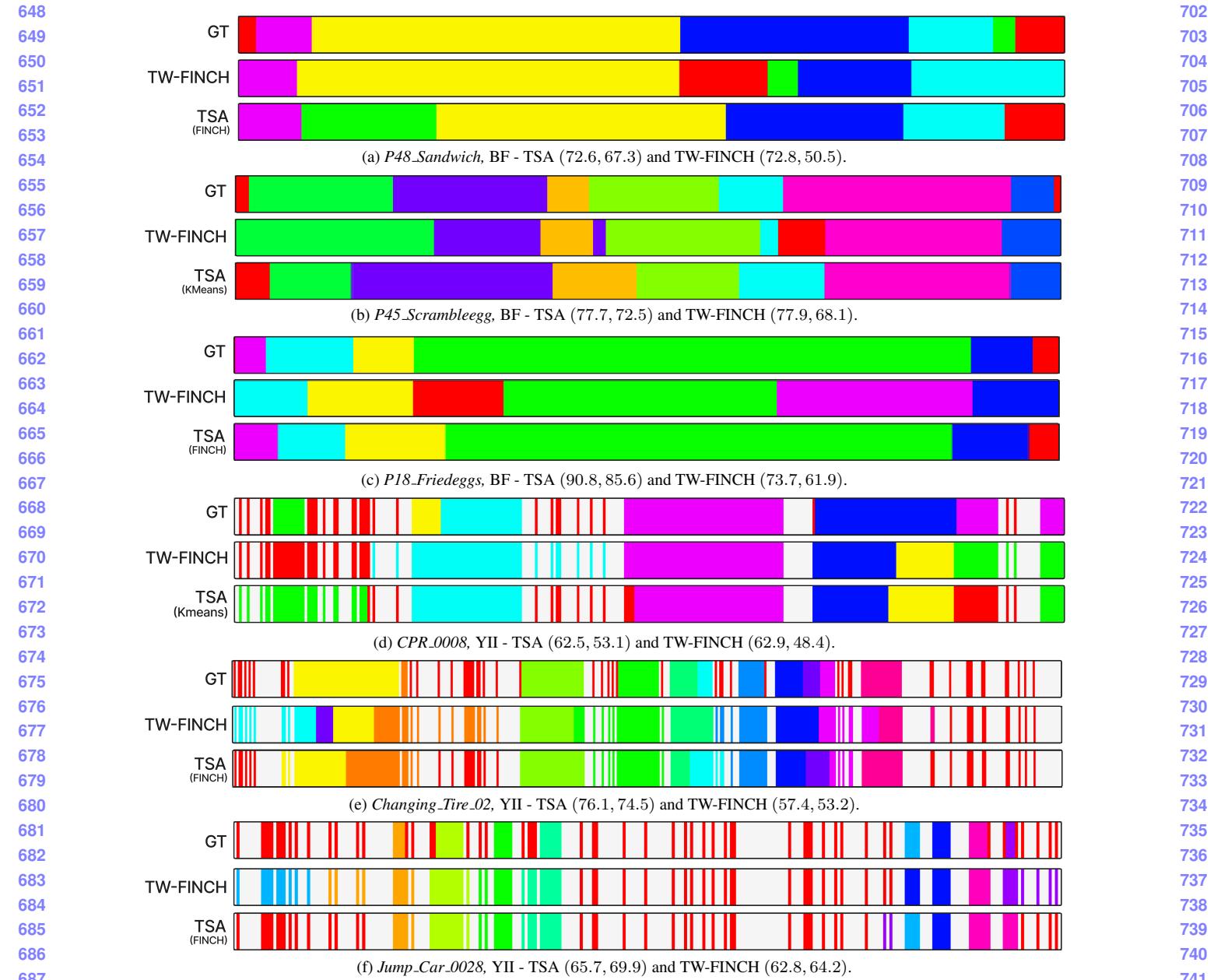


Figure 4. Segmentation output comparisons on two sample videos from BF and YII. Each caption shows the name of the video and the results (x, y) which are (MoF, F1) for each example.

5. Conclusions

This paper introduced a novel fully unsupervised approach for learning action representations in complex activity videos that solely operates on a single unlabelled input video. Our method exploits the temporal proximity and the semantic similarity in the initial feature space to discover the representational clustering grounding action segmentation. Our key contributions are a shallow architecture and a triplet-based loss with a triplet-based selection mechanism based on similarity distribution probabilities to model tem-

poral smoothness and semantic similarity within and across actions. Experimental results on the BF and the YII datasets demonstrated that the learned representations, followed by a generic clustering algorithm, achieve SoTA performance. Furthermore, it has the advantage of not requiring human annotations, is easy to train and does not present domain adaptation issues. Future work will consider how to jointly learn the action clusters and the representation as well as how to build on representations learn at the video-level to match videos at the activity-level.

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