Hierarchical Attention Network for Action Segmentation

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Abstract

Temporal segmentation of events is an essential task and a precursor for the automatic recognition of human actions in the video. Several attempts have been made to capture frame-level salient aspects through attention but they lack the capacity to effectively map the temporal relationships in between the frames as they only capture a limited span of temporal dependencies. To this end we propose a complete end-to-end supervised learning approach that can better learn relationships between actions over time, thus improving the overall segmentation performance. The proposed hierarchical recurrent attention framework analyses the input video at multiple temporal scales, to form embeddings at frame level and segment level, and perform fine-grained action segmentation. This generates a simple, lightweight, yet extremely effective architecture for segmenting continuous video streams and has multiple application domains. We evaluate our system on multiple challenging public benchmark datasets, including MERL Shopping, 50 salads, and Georgia Tech Egocentric datasets and achieves state-of-the-art performance. The evaluated datasets encompass numerous video capture settings which are inclusive of static overhead camera views and dynamic, ego-centric head-mounted camera views, demonstrating the direct applicability of the proposed framework in a variety of settings.

Keywords:

1. Introduction

Actions performed by humans are continuous in nature, and different actions flow seamlessly from one to another as a person completes one or more tasks. Hence when designing intelligent surveillance systems it is crucial to utilise robust and efficient action segmentation mechanisms to recognise human actions from those continuous streams. Such a system is not only beneficial for detecting suspicious activities in a surveillance setting but also vital for numerous tasks including elder care monitoring, human-robot interactions and warehouse automation.

Action segmentation algorithms should exploit the idea that individual actions in a continuous sequence are often related to its surrounding action. For example, when performing an activity such as shopping, the action ‘inspect item on shelf’ may be followed by the actions ‘put item in basket’. However, it may also witness a ‘theft’ event. Each action is related and dependant on what has previously happened, as such, capturing the relations among those actions facilitates the segmentation process.

Most existing approaches for continuous action segmentation (Lea et al., 2016a; Singh et al., 2016a) use features extracted from Convolution Neural Networks (CNNs), at each frame, and map them temporally through Recurrent Neural Network (RNN) models. However such naive temporal modelling has been shown to capture a limited span of temporal dependencies (Singh et al., 2016a). Temporal Convolution Networks (TCNs) (Lea et al., 2017) have been introduced to capture attention at a frame level and are further augmented in Ding and Xu (2017) through a hybrid of both TCN and RNN to model...
dependencies at multiple temporal scales. However one obvious drawback of this architecture is that it has the overhead of learning the temporal attention values of the TCN kernels as well as the RNN parameters for long-term dependencies.

In contrast we introduce a simpler, yet effective hierarchical attention framework which learns both frame level and segment level attention parameters in an unsupervised manner. The proposed framework is shown in Fig. 1. The hierarchical network architecture is motivated by Li et al. (2015a) and Sordoni et al. (2015) and shows the ability to learn the temporal correspondences of the extracted CNN spatial features while learning relationships between actions that facilitate the overall action segmentation task.

As shown by Fig. 1, we perform frame level embedding on sub-segments of the video at the first level of the hierarchy and utilise frame attention weights $\alpha_{i,t}$ (where $i$ - number of segments and $t$ - number of frames in each segment), to retain only significant information when deriving the segment level embeddings. At the next stage, these segments are combined and compressed using a series of segment attention weights $\alpha_i$ in order to generate a representation for each video sequence. At the decoding stage, we expand these representations at each level of the hierarchy and finally at the frame level decoding we map the representation to a class label. Hence, our end-to-end model maps the sequence of video frame features directly to class labels and is able to compete with the current state-of-the-art models.

Our main contributions are listed as follow:

- We propose a novel hierarchical recurrent model that performs end-to-end continuous fine-grained action segmentation.
- We introduce an attention framework that effectively embeds salient frame level and video segment level spatio-temporal features to facilitate the overall action segmentation task.
- We achieve state-of-the-art results for three challenging datasets: MERL shopping, 50 salads, Georgia Tech Egocentric dataset.
- We conduct a series of ablation experiments to demonstrate the importance of different components of the proposed hierarchical model.

Due to the lack of availability of annotated data from real-world surveillance videos, we utilise the MERL Shopping (Singh et al., 2016a), 50 salads (Stein and McKenna, 2013), and Georgia Tech Egocentric (Li et al., 2015b) datasets in our evaluations. However with the inclusion of MERL Shopping dataset which mimics a surveillance setting, captured through an overhead camera; the dynamic egocentric camera view provided through a head-mounted camera in the Georgia Tech Egocentric dataset and the home monitoring system instantiated in the 50 salads dataset, our evaluations suggest the direct application of the proposed architecture in any surveillance setting with either static or dynamic camera views is possible.

2. Related work

Action recognition can be broadly grouped into two main categories: Discrete (Delaitre et al., 2010) Simonyan
and Zisserman, 2014; Gammulle et al., 2017, 2019b) and continuous fine-grained action recognition (Lea et al., 2017; Ni et al., 2014; Zhou et al., 2014, 2015; Gammulle et al., 2020, 2019a) approaches. Discrete action recognition is performed on pre-segmented video sequences containing one action per video while continuous fine-grained models are evaluated on untrimmed video sequences containing more than one action per video. Since actions occurring in the real world are continuous in nature finding solutions to continuous fine-grained action recognition is more important and is also more challenging as it requires both localisation and recognition of the action frames. We therefore focus on continuous fine grained action scenarios in this paper.

In early literature on continuous action recognition, most works utilise hand-crafted features such as HOG, HOF, MBH, Trajectory or pose based features for the action segmentation task (Fernando et al., 2015; Rohrbach et al., 2012). Apart from these, human-object interactions have been considered in (de La Gorce et al., 2008; Trinh et al., 2012) by taking hand-object related features into account. However, these methods lack the ability to capture rich contextual information among various objects during interactions. Zhou et al. (2014) introduced a model to overcome these limitations, capturing joint distributions between motion and objects-in-use informations.

Most recently with the introduction of deep learning, researchers have focused on utilising deep neural networks for feature extraction and temporal mapping. For instance, Singh et al. (2016a) utilise multiple Convolution Neural Networks (CNNs) for feature extraction from multiple input feature streams at the frame level and map their temporal dependencies through a bi-directional Recurrent Neural Network (RNN). Wu et al. (2018a) investigated Convolutional RBMs for feature extraction from video frames. In Wu et al. (2018a,c) the authors propose spatially recurrent architectures for deep feature embedding and Wu et al. (2018b) investigated Gated Recurrent Unit (GRUs) coupled with location-based attention as a method for feature extraction. However, Lea et al. (2017) demonstrate the limited attention span of native RNN architectures and several architectures have been proposed using Temporal Convolution Networks (TCN) (Lea et al., 2017, 2016c) for generating the required frame level attention, and they are further augmented in Ding and Xu (2017) with a hybrid of TCN and RNN to overcome the fixed temporal attention span of the TCN model.

However we observe several draw backs of these architectures. Firstly the TCN attention mechanism considers fixed, short temporal windows when embedding the input frames. Furthermore, the introduction of bi-directional RNN in Ding and Xu (2017) to map long-term temporal relationships inherits the additional overhead of training both TCN and RNN models to propagate the frame level information to the decoder model. In addition, several prior works have shown naive RNN architecture without an attention mechanism to loose long-term relationships and focus only on the last few time-steps (Kumar et al., 2016; Fernando et al., 2018). In contrast, we propose a simple and light weight approach using a hierarchical attention framework to encode the salient spatio-temporal information effectively. We capture our inspiration from the natural language processing domain where they illustrate the efficiency of hierarchical representation learning when handling lengthier sequences.

Hierarchical learning with time series data has been extensively investigated as it provides a richer context representation compared to standard unstratified learning (Deng et al., 2016a). For instance in Deng et al. (2016a), the authors investigated the hierarchical learning paradigm by coupling deep learning together with reinforcement learning to model human behaviour in financial asset trading. They illustrated that a deep recurrent neural network front end for their proposed framework is more effective for learning informative features from time series data. A similar observation is reported in Deng et al. (2016b), where the authors propose to hierarchically encode the information derived from both neural and fuzzy system to generate a richer embedding. The effectiveness of this approach is validated on different machine learning tasks including image categorisation, segmentation and financial data prediction.

When considering image based works, You et al. (2014) proposed to use a hierarchical metric learning approach for object detection. An approach which simultaneously learns a distance metric for inter-video and intra-video distances, which could also be seen as hierarchical representation learning from videos, is proposed in Zhu et al. (2018). In a different line of work, the authors in Yu et al. (2018) have looked at pooling features from multiple level of the hierarchy to create an informative feature embedding. However, none of the related works on
video based recognition have looked into utilising a hierarchical attention framework when extracting these informative features from frame embeddings. To the best of our knowledge, only a single-level of attention [Yang et al., 2017] is utilised for most computer vision tasks. Furthermore, our model does not inherit any deficiencies of image based methods as in Deng et al. (2013), and is capable of handling long video sequences of RGB frames without losing information.

The utilisation of the hierarchical attention allows us not only to achieve better efficiency compared to Ding and Xu (2017), but also to gain comparatively better results on standard benchmarks.

3. Methodology

Following (Lea et al., 2017) we formulate the action segmentation task as a multi-class classification problem, where we generate an action classification for every frame in a video. Motivated by the impressive results from Li et al. (2015a) and Sordoni et al. (2015) for embedding long term temporal information in text synthesis and language modelling tasks, we develop a new hierarchical attention framework as an encoder-decoder framework capturing spatio-temporal information in the input video. We model the dependencies between frames at multiple levels, namely frame-level and segment-level, through the proposed hierarchical attention framework as follows.

3.1. Frame-level embedding

The frame-level embedding is performed by first extracting salient spatial features from a CNN model. Let the video sequence ($X$) contain $i$ ($i \in [1, N]$) segments, each containing $t$ ($t \in [1, T]$) frames. Then for each frame $x_{i,t}$ in video $X$ ($X = \{x_{1,1}, x_{1,2}, \ldots, x_{N,T}\}$) CNN features ($e_{i,t}$) are extracted as follows,

$$e_{i,t} = CNN(x_{i,t}).$$

(1)

The extracted frame-wise CNN features are then passed through the first encoder LSTM which generates an embedding output for each segment.

$$h_{i,t}^{encode} = LSTM(e_{i,t}, h_{i,t-1}^{encode}),$$

(2)

where $h_{i,t}^{encode} \in \mathbb{R}^{L \times 1}$.

Then we apply frame level attention to capture different levels of salient action features from different frames.

$$u_{i,t}^{encode} = tanh(\hat{W}h_{i,t}^{encode} + \hat{b}),$$

(3)

where $\hat{W} \in \mathbb{R}^{L \times 1}$ and $\hat{b}$ are weight and the bias of a multi layer perceptron (MLP), and $u_{i,t}^{encode}$ is the hidden representation of the one layer MLP for frame embedding $h_{i,t}^{encode}$. Then the similarity of $u_{i,t}^{encode}$ with the frame level context vector $\hat{u}$ is measured and normalised through a softmax function given by,

$$\alpha_{i,t} = \frac{exp([u_{i,t}^{encode}]^T, \hat{u})}{\sum_{j=1}^{T} exp([u_{i,j}^{encode}]^T, \hat{u})}.$$  

(4)

The frame level context vector can be seen as a higher level representation of the context of those frames. $\hat{u}$ is randomly initialised and jointly trained during the training process. These weighted embeddings are then used to generate the segment embedding of the $i_{th}$ video segment as follows,

$$s_{i} = \sum_{j=1}^{T} \alpha_{i,j}h_{i,j}^{encode}.$$  

(5)

3.2. Segment-level embedding

Given the segment embedding, $s_{i}$, video embedding can be performed as follows,

$$h_{i}^{encode} = LSTM(s_{i}, h_{i-1}^{encode}).$$

(6)

Different video segments will have different levels of visual clues when recognising the video actions. Therefore similar to, Equations 4 and 5, we quantify the importance of each segment using attention,

$$u_{i}^{encode} = tanh(\hat{W}h_{i}^{encode} + \hat{b}),$$

(7)

$$\alpha_{i} = \frac{exp([u_{i}^{encode}]^T, \hat{u})}{\sum_{j=1}^{T} exp([u_{j}^{encode}]^T, \hat{u})},$$

(8)

$$\nu = \sum_{j=1}^{T} \alpha_{j}h_{j}^{encode},$$

(9)

where $\hat{u}$ is the segment level context vector and $\nu$ is the embedding that summarises the overall video sequence, $X$. 

4
3.3. Decoders

After generating a video level embedding, representing the context of the entire input video, we need to decode this information to generate the frame level class labels, segmenting the video into action classes. Similar to the encoding process we attend to the decoding in two levels, segment level decoding and frame level decoding. First we initialise the initial hidden state \( h_{\text{decode}}^0 \) of the segment level decoder using the video embedding \( v \) (i.e. \( h_{\text{decode}}^0 = v \)) and generate the segment level decoding as follows,

\[
h_{\text{decode}}^i = \text{LSTM}(s_i, h_{\text{decode}}^{i-1}).
\]

Then at the next level frame level decoding is done through,

\[
h_{\text{decode}}^{i,t} = \text{LSTM}(e_{i,t}, h_{\text{decode}}^{i,t-1}),
\]

where \( h_{\text{decode}}^{i,0} = h_{\text{decode}}^N \). Finally, we generate the class label for each frame using,

\[
P = \text{softmax}(h_{\text{decode}}^{i,t}).
\]

4. Experimental Results

4.1. Datasets

The evaluations have been performed by utilising the following fine-grained continuous action video datasets, containing multiple actions within each video sequence.

4.1.1. MERL Shopping dataset \(\text{(Singh et al., 2016a)}\)

The MERL Shopping dataset consists of 96 videos, each with a duration of 2 minutes. The videos have been recorded by a static overhead video camera, and show 32 different subjects shopping from grocery store shelving units. These videos includes five different action classes: ‘Reach to Shelf’, ‘Retract from Shelf’, ‘Hand in Shelf’, ‘Inspect Product’ and ‘Inspect Shelf’. Training, testing and validation splits are as in \(\text{Singh et al. (2016a)}\)

4.1.2. The University of Dundee 50 salads dataset \(\text{(Stein and McKenna, 2013)}\)

50 salads dataset contains 25 users, each appearing two times making a salad. These 50 videos are captured through a static RGBD camera pointed at the user and last up to 10 minutes. Along with the visual and depth information the authors have captured accelerometer data, however, only the video data is used for evaluations. We considered all seventeen mid-level action classes together with the background class. Training, testing and validation splits are as in \(\text{Stein and McKenna (2013)}\).

4.2. Georgia Tech Egocentric Activities Dataset \(\text{(Li et al., 2015b)}\)

In contrast to the static overhead camera view of the previous 2 datasets, this dataset contains videos recorded from a head mounted camera and includes four subjects performing seven different daily activities. We utilise 11 action classes defined in \(\text{Li et al. (2015b)}\) including the background class.

4.3. Evaluation Metrics

The evaluations are performed utilising both segmentation and frame-wise metrics. Even though the frame-wise metric has been widely used, due to different segmentation behaviour, models with similar frame-wise accuracies can often show high visual dissimilarities (Lea et al., 2017). As such we also utilise segmentation metrics such as segmental F1 score (F1@k) (Lea et al., 2017), segmental edit score (edit) (Lea et al., 2016b) and mean average precision with midpoint hit criterion (mAP@mid) (Singh et al., 2016a; Rohrbach et al., 2016). Depending on the availability of the baseline model results we use different combinations of these metrics when evaluating different datasets.

4.4. Implementation details

For CNN feature extraction we utilised ResNet101 (He et al., 2016), which has been pre trained on the ImageNet database (Russakovsky et al., 2015), and extracted 2048 dimensional feature vectors from the final average pooling layer per frame. These features are then passed through a fully connected layer with 200 hidden units to reduce the input feature dimension to 200.

At the first stage of the encoding we sequentially pass input features through the first layer of the encoder with 200 hidden units in order to generate frame level embedding (see Fig. 1). In the next level of the hierarchy these embeddings are combined and compressed to represent the segment level representation with 200 hidden units.
the final level of the encoder we represent the entire video with 200 units. For each level in the decoder we utilise the same hidden unit dimensions as the encoder. The proposed HA_Net model is implemented with the Keras (Chollet et al., 2015) deep learning library with Theano (Bergstra et al., 2010) backend. The network is trained using categorical cross-entropy loss with stochastic gradient decent and the Adam optimiser (Kingma and Ba, 2014), and initialised using default Keras settings.

4.5. Results

The evaluation results for MERL Shopping (Singh et al., 2016a), 50 salads (Stein and McKenna, 2013) and Georgia Tech Egocentric (Li et al., 2015b) datasets are presented in Tables 1, 2 and 3, respectively.

For MERL Shopping, as the first baseline we use the method introduced by (Singh et al., 2016a), for which we use the re-evaluated results provided in Lea et al. (2017) for frame-wise and segmentation metrics. ‘MSN Det’ denotes the results for the sparse model proposed in Singh et al. (2016a) whereas ‘MSN Seg’ denotes the dense (per frame) action segmentation model.

When observing the results presented in Table 1 we observe poor performance from MSN Det and MSN Seg models, especially among F1 scores, mainly due to the over segmentation of the input video. This is largely because the long-term temporal dependencies cannot be captured through a naive recurrent structure such as a bi-directional LSTM. The model ED-TCN (Lea et al., 2017) has been able to overcome these deficiencies by incorporating Temporal Convolutional Networks (TCN) where they utilise multiple attention scales to capture salient spatio-temporal information.

However, when observing the results presented in Tables 2 and 3 it is clear that the ED-TCN model doesn’t fully capture the temporal context presented in the video segment. The model fails to capture long-term dependencies among different action classes in the given video due to its fixed receptive field size. TricorNet (Ding and Xu, 2017) tackles this issue through a hybrid of TCN and RNN. In order to capture long-term dependencies they pass the TCN embeddings through a bi-directional LSTM.

The proposed method shows similarity to the TricorNet model by the utilisation of the encoder-decoder framework, and by using LSTMs to map the temporal accor-

| Methods               | F1@10,25,50 | mAP@mid | Accuracy |
|-----------------------|-------------|---------|----------|
| MSN Det [Singh et al. (2016a)] | 46.4, 42.6, 25.6 | 81.9 | 64.6 |
| MSN Seg [Singh et al. (2016a)] | 80.0, 78.3, 68.4 | 69.8 | 76.3 |
| Dilated TCN [Lea et al. (2017)] | 79.9, 78.0, 67.6 | 75.6 | 76.4 |
| ED-TCN [Lea et al. (2017)] | 86.7, 85.1, 72.9 | 74.4 | 79.0 |
| Proposed HA_Net       | 80.9, 78.1, 71.2 | 76.7 | 79.3 |

Table 1: Action segmentation results for MERL Shopping dataset Singh et al. (2016a). Best values are in bold and the second best values are underlined.

| Methods               | F1@10,25,50 | mAP@mid | edit | Accuracy |
|-----------------------|-------------|---------|------|----------|
| Spatial CNN [Lea et al. (2016a)] | 32.3, 27.1, 18.9 | 24.8 | 54.9 |
| IDT+LM [Richard and Gall, 2016] | 44.4, 38.9, 27.8 | 45.8 | 48.7 |
| Dilated TCN [Lea et al. (2017)] | 52.2, 47.6, 37.4 | 43.1 | 59.3 |
| ST-CNN [Lea et al. (2016a)] | 55.9, 49.6, 37.1 | 45.9 | 59.4 |
| Bi-LSTM [Lea et al. (2017)] | 62.6, 58.3, 47.0 | 55.6 | 55.7 |
| ED-TCN [Lea et al. (2017)] | 66.0, 59.3, 52.6 | 59.8 | 64.7 |
| TricorNet [Ding and Xu, 2017] | 76.1, 72.7, 56.6 | 62.8 | 67.5 |
| Proposed HA_Net       | 68.2, 67.3, 56.8 | 61.8 | 67.8 |

Table 2: Action segmentation results for 50 salads dataset Stein and McKenna (2013). Best values are in bold and the second best values are underlined.

| Methods               | F1@10,25,50 | mAP@mid | edit | Accuracy |
|-----------------------|-------------|---------|------|----------|
| EgoNet+TDD [Singh et al. (2016b)] | NA | 64.4 |
| Spatial CNN [Lea et al. (2016a)] | 41.8, 36.0, 25.1 | 54.1 |
| ST-CNN [Lea et al. (2016a)] | 58.7, 54.4, 41.9 | 60.6 |
| Dilated TCN [Lea et al. (2017)] | 58.8, 52.2, 42.2 | 58.3 |
| Bi-LSTM [Lea et al. (2017)] | 66.5, 59.0, 43.6 | 58.3 |
| ED-TCN [Lea et al. (2017)] | 72.2, 69.3, 56.0 | 64.0 |
| TricorNet [Ding and Xu, 2017] | 76.0, 71.1, 59.2 | 64.8 |
| Proposed HA_Net       | 73.6, 68.0, 60.1 | 64.3 |

Table 3: Action segmentation results for Georgia Tech Egocentric dataset Li et al. (2015b). Best values are in bold and the second best values are underlined.
dance of the inputs. However, we would like to point out that the proposed method contains fewer trainable parameters when compared to TricorNet due to TricorNet’s use of convolution and bidirectional LSTM layers. The proposed method is very time efficient as a result of hierarchically compressing the input information in the encoding process through the proposed hierarchically attention framework (for more details regarding time complexity please refer to Section 4.9).

Despite being light weight it achieves comparative results to TricorNet due to the careful design of the proposed hierarchical attention framework. The encoder of TricorNet utilises 1D convolutions and pooling to hierarchically embed the features from input frames. However, these fail to capture the temporal relationships between consecutive frames, and fail to determine the salient information that should be passed through the hierarchy when generating feature embeddings. Hence, even though TricorNet is a more complex network, it fails to generate superior results. In contrast, using the proposed hierarchical attention framework we force the network to learn temporal relationships at multiple granularities allowing us to capture an informative feature vector with lower complexity.

4.6. Ablation Experiment

To further demonstrate the proposed method we constructed a series of ablation models by strategically removing certain components from the proposed approach (HA_Net) as follows:

- **HA_Net-VE**: We remove the segment-level embedding (see Sec. 3.2) component, performing only frame-level embedding.
- **HA_Net - (VE, SE)**: From the previous model we removed frame-level attention mechanism (i.e Eq. 3 to 5). Therefore the model is a naive LSTM model, which uses only the proposed encoder to simply map frame-level embeddings to action classes without using any attention.

We evaluated these models against the test set of MERL Shopping dataset [Singh et al., 2016a] and the evaluation results are presented in Table 4. When observing the results presented, we observe poor performance from the HA_Net- (VE, SE) indicating the deficiencies of naive temporal modelling with the recurrent architectures. We improve upon these results in HA_Net-VE model with the aid of frame level attention through Eq. 3 to 5. We would like to compare results of this model with the results presented in Table 4. It is clear that even frame level attention is sufficient to overcome the shortcomings of the naive RNN models such as MSN Det and MSN Seg. However, with the addition of segment level attention the proposed method maps the temporal relationships at multiple temporal scales, allowing us to overcome the limitations with the TCN architectures such as ED-TCN and TricorNet and outperform all the considered baselines.

| Model            | F1@10,25,50 | mAP@mid | Accuracy |
|------------------|-------------|---------|----------|
| HA_Net - (VE, SE)| 72.8, 72.0, 68.4 | 66.5     | 71.3     |
| HA_Net - VE      | 73.5, 72.8, 70.0 | 73.8     | 77.6     |
| HA_Net           | 80.9, 78.1, 71.2 | 76.7     | 79.3     |

Table 4: HA_Net Vs (HA_Net)-VE (Network without video level embedding)

4.7. Hyperparameter evaluation

The frame level, segment level and video level embedding dimensions are of equal size and this embedding dimension L is evaluated experimentally, and is shown in Fig. 2 (a). As L = 200 produces the highest mAP we utilise this as the embeddings size for all the experiments. With a similar experiment we evaluate the number of frames within a segment, T; and number of segments N, and these results are shown in Fig. 2 (b) and (c), respectively. As such T is set to be 50 and N is chosen to be 5. In these experiments we use the the validation set of the MERL Shopping dataset. We tune each parameter while holding the others constant.

As shown in Fig. 2 (b), when the number of frames that are considered is less the accuracies are lower, due to the fact that few frames provides less temporal cues for the action segmentation. Hence, with the number of frames (T), the accuracy gradually increases until T=50. Beyond that point the accuracy tends to decrease slowly. This is mainly due to the reason that when mapping longer sequences into a finite size frame level vector through an LSTM can cause information loss. However when considering short segments of the sequence, utilising the proposed attention mechanism, we can map the fine-grained details in to the frame-level embedding vector.
In Fig. 2(c), when the number of segments is set lower, the segment embedding contains less information which makes the decoding process more difficult. Also when the number of segments is higher, it tends to confuse the model with too much information. When evaluating, we found that the optimal value for \( N = 5 \), which provides satisfactory information for the segmentation process. These values of \( T = 50 \) and \( N = 5 \) have been utilised when evaluating the model for all three datasets.

4.8. Qualitative results

Qualitative results of the proposed model on MERL Shopping (Singh et al., 2016a), 50 salads (Stein and McKenna, 2013) and Georgia Tech Egocentric (Li et al., 2015b) datasets are presented in Figures 3, 4 and 5 respectively. We observe slight confusion between action classes, typically at the event boundaries where it is quite difficult to determine the action transitions. However in general we observe that all the action classes are being detected and false detections only last for short periods of time.

4.9. Time efficiency

The proposed approach has only 13.5M parameters. We ran the test set of the MERL shopping dataset on single core of an Intel E5-2680 2.50GHz CPU and the model generates 1000 predictions, with \( 50 \times 5 = 250 \) frames in each prediction, in 21.2 seconds.

5. Conclusion

We have introduced a novel hierarchical attention framework for segmenting human actions in videos. The proposed framework spans its’ attention across multiple temporal scales, embedding the context information as a vector representation of the video. The decoder model hierarchically decodes this embedded information, effectively propagating the salient aspects to the classification module. Our empirical evaluations on MERL Shopping, 50 salads, and Georgia Tech Egocentric datasets clearly demonstrates the effectiveness of the proposed method in different application domains including intelligent surveillance and home monitoring. The ablation experiments suggest the importance of the bottom up computational process, through frame level to video level compression of the video embeddings, allowing the model to explicitly learn the long-term temporal dependencies.

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Figure 2: Evaluation of hyper-parameters: We use the the validation set of the MERL Shopping dataset and tune each parameter (i.e $L$, $T$ and $N$) while holding the others constant. As $L = 200$, $T=50$ and $N=5$ produce best results we utilise these values for evaluating the model for all three datasets.

Figure 3: Action segmentation results for MERL Shopping [Singh et al. 2016a] dataset

Figure 4: Action segmentation results for 50 salads [Stein and McKenna 2013] dataset

Figure 5: Action segmentation results for Georgia Tech Egocentric [Li et al. 2015b] dataset
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