Abstract

Action recognition is currently one of the top-challenging research fields in computer vision. Convolutional Neural Networks (CNNs) have significantly boosted its performance but rely on fixed-size spatio-temporal windows of analysis, reducing CNNs temporal receptive fields. Among action recognition datasets, egocentric recorded sequences have become of important relevance while entailing an additional challenge: ego-motion is unavoidably transferred to these sequences. The proposed method aims to cope with it by estimating this ego-motion or camera motion. The estimation is used to temporally partition video sequences into motion-compensated temporal chunks showing the action under stable backgrounds and allowing for a content-driven temporal sampling. A CNN trained in an end-to-end fashion is used to extract temporal features from each chunk, which are late fused. This process leads to the extraction of features from the whole temporal range of an action, increasing the temporal receptive field of the network. This document is best viewed offline where some figures play as animation.

1. Introduction

Video action classification is a highly emerging research topic in computer vision [8, 1, 10] due to its potential wide range of applications.

Among reported approaches, those relying on the use of Convolutional Neural Networks (CNNs) have reported the highest performances. These methods are based on the extraction of spatio-temporal features on the video, which are then used to classify the action recorded. Due to processing constraints, these features are instead usually extracted on video segments, i.e. fixed-size spatio-temporal windows obtained by sampling and cutting the video, hence discarding the rest of the video sequence. CNNs with reduced temporal receptive fields emerge from this design criteria.

There are several video action classification datasets in the literature, among them, egocentric ones, i.e. those recorded from a first person point of view, have become of crucial importance [2]. The egocentric domain presents a set of relevant advantages with respect to third-person recordings. The point of view in egocentric videos, closely related to the position of humans eyes, provides a view similar to what of what we humans actually see. Besides, the close proximity of the wearable camera to the undergoing activity brings up the necessity to cope with ego-motion-

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action provides closer and more detailed objects representations compared to third-person view recordings.

However, egocentric recordings entail an additional challenge: human body or ego-motion is inevitably transferred to video sequences (see left column in Figure 1), creating motion and temporal patterns that may occlude or befoul the action’s ones. This ego-motion might hinder the performance of modern CNNs trained to recognize actions in videos [9, 4, 11, 12] as these are focused on extracting the action’s ones. This ego-motion might hinder the performance of modern CNNs trained to recognize actions in videos [9, 4, 11, 12] as these are focused on extracting the representative temporal features defining an action.

Our proposal aims to cope with ego-motion problems while providing a sequence-driven adaptive temporal sampling scheme. This process aims to filter out the majority of the ego-motion, leading to an action segment with a quasi-static background. Camera motion compensation accentuates the representative motion in a specific action, such as the movement of objects or hands (Figure 1), which might lead to more representative and distinguishable action features. In addition, we use the camera motion estimation to temporally divide the sequence into representative context temporal chunks. This temporal partitioning benefits the feature extraction process by: 1) Easing the process of camera motion compensation by having chunks that represent contextually similar backgrounds with limited camera motion. 2) Enabling the use of an irregular temporal sampling policy hence expanding the CNN temporal receptive field. We adopt a shared end-to-end fashion CNN to independently analyze each of the camera motion compensated chunks. Finally, features from each chunk are late fused to obtain final action predictions.

Figure 3. Camera motion estimation example. Each black dot corresponds to the projected middle coordinates of a frame using homography with respect to a reference frame. X and Y axes represent normalized spatial movement while Z axis represents time in frame scale. Best viewed in Adobe Reader where figure should play as animation.

2. Method

Four different stages are posed for the action classification task. First, camera motion is estimated for an action video sequence (Section 2.1). Then, the resulting estimation is used to partition the original video sequence into temporal chunks via unsupervised clustering (Section 2.2). Camera motion is then compensated for each temporal chunk independently (Section 2.3). Finally, motion compensated chunks are fed to a CNN which obtains the final predictions (Section 2.4). The proposed pipeline is depicted and detailed in Figure 2.
2.1. Camera Motion Estimation

We estimate the camera motion of a given sequence by using a classical stereo image rectification technique [6]. First, a pre-trained D2Net CNN [3] is used to obtain reliable pixel-level features for each video frame. Features of every frame are then matched to the ones from a chosen reference one—typically the first or the last frame. These matching correspondences are used to compute planar homographies using RANSAC [5]. So-extracted homographies define the transforms between every frame and the reference frame. An estimation of the camera motion during the sequence is obtained by projecting the middle point coordinates from every frame using the corresponding homography (Figure 3).

Video sequences might include high camera motion in terms of panning or tilting. This severe motion leads to high background variation along frames, hindering computation of a motion-compensated sequence. To overcome this issue we propose to divide each video sequences into different temporal chunks using unsupervised clustering.

2.2. Unsupervised Partition in Temporal Chunks

Unsupervised clustering is performed using the KMeans technique [7] fed by the spatio-temporal coordinates extracted in the camera motion estimation stage. By this, the temporal span of a video sequence is reduced and the original video sequence is divided into smaller parts with contextually similar backgrounds. An example of this process is depicted in Figure 4.

2.3. Camera Motion Compensation

The image rectification process described in section 2.1 is performed individually for each chunk reusing the features there extracted but defining a new reference frame for each chunk. Using the new obtained homographies, the frames in a chunk are warped to its chunk-reference frame to a camera motion compensated chunk (Figure 1 right column). These compensated chunks are the ones used for the end-to-end training of the shared Convolutional Neural Network (CNN). The proposed technique for camera motion compensation and sequence partition into chunks is highly improvable. This is a first approach to prove that this benefits the action recognition process.

2.4. CNN Architecture

To obtain temporal features from chunks the Slow-Fast ResNet-50 CNN [4] is used as backbone. The Slow-Fast is composed by the Spatial branch and the Temporal branch. For our participation, due to some computational constraints, we have only explored the use of the Temporal branch CNN. This branch expands temporal channels while reducing the spatial ones, ensuring that final features are closer to the temporal domain than to the spatial one.

Each chunk is independently fed-forwarded to the same 3D CNN to obtain features. Chunk features are later fused through concatenation to obtain a final feature vector. The use of chunks leads to the extraction of features from the whole temporal range of the action, hence increasing the temporal receptive field of the network with respect to analyzing only a fixed-size temporal window.

Two different fully-connected layers and regular logarithmic softmax are used to obtain verb (v) and noun (n) probabilities \( p_v \) and \( p_n \) respectively. \( p_v \) and \( p_n \) are used to obtain action predictions as:

\[
p_a = p_v \odot p_n, \tag{1}
\]

where \((\odot)\) is defined as the outer product between two vectors.

Inspired by the approaches in [12, 13], we re-weight action probabilities \( p_a \) by using training priors. These priors represent the probability \( p_p(v, n) \) of a pair verb-noun being an action in the training set. Unobserved actions as "peeling knife" have \( p_p(v, n) = 0 \) whereas observed actions as "open door" have \( p_p(v, n) = 1 \). Final action probabilities are computed as:

\[
p_a = p_p(v, n) \odot (p_v \odot p_n), \tag{2}
\]

where \((\odot)\) represents the Hadamard product.

2.5. Training Procedure

Given that the Challenge needs separate predictions for verb, noun and action, we have decided to train the action classification CNN in a multi-task fashion. The final loss guiding the training process is computed as:
Table 1. Preliminary results. (%)

| Method   | Number of Parameters | Top@1 Action | Top@1 Verb | Noun Action | Noun Verb | Top@5 Action | Top@5 Verb | Noun |
|----------|----------------------|--------------|------------|-------------|-----------|--------------|------------|------|
| Baseline | 0.8 M                | 29.00 %      | 52.44 %    | 40.78 %     | 48.22 %   | 85.56 %      | 67.78 %    | 66.91 % |
| Ours     | 1 M                  | 30.25 %      | 54.56 %    | 42.67 %     | 49.67 %   | 85.33 %      | 66.89 %    | 67.28 % |

Table 2. EPIC Kitchens Seen Test S1 results. (%)

| Team          | Position | Top@1 Verb | Top@1 Noun | Top@5 Verb | Top@5 Noun | Precision Verb | Precision Noun | Recall Verb | Recall Noun | Action Verb | Action Noun | Action |
|---------------|----------|------------|------------|------------|------------|----------------|----------------|-------------|-------------|-------------|-------------|--------|
| UTSBaidu      | 1        | 70.41      | 52.85      | 42.57      | 90.78      | 76.62          | 63.55          | 47.11       | 24.94       | 45.82       | 50.02      | 26.93  |
| NUS CVML      | 2        | 66.56      | 49.60      | 41.59      | 90.10      | 72.45          | 62.23          | 45.45       | 21.82       | 47.19       | 45.84      | 24.34  |
| FBK HuPBA     | 3        | 68.68      | 49.35      | 40.00      | 90.97      | 72.45          | 62.23          | 45.45       | 21.82       | 47.19       | 45.84      | 24.34  |

Table 3. EPIC Kitchens Unseen Test S2 results. (%)

| Team          | Position | Top@1 Verb | Top@1 Noun | Top@5 Verb | Top@5 Noun | Precision Verb | Precision Noun | Recall Verb | Recall Noun | Action Verb | Action Noun | Action |
|---------------|----------|------------|------------|------------|------------|----------------|----------------|-------------|-------------|-------------|-------------|--------|
| UTSBaidu      | 1        | 60.43      | 37.28      | 27.96      | 83.07      | 63.67          | 46.81          | 35.23       | 28.41       | 14.82       | 14.93       | 2.87   |
| GT WISC MPI   | 2        | 60.05      | 38.14      | 27.35      | 81.97      | 63.81          | 45.24          | 33.59       | 21.29       | 10.84       | 13.95       | 7.14   |
| NUS CVML      | 3        | 54.56      | 33.46      | 26.97      | 80.40      | 60.98          | 46.43          | 30.54       | 14.99       | 25.28       | 28.39       | 17.97 |

with \( L = L_a + L_v + L_n \), \( (3) \)

3. Experiments

3.1. Implementation

3.1.1 Training

For the spatial domain each input image is adapted to the network input by resizing the smaller edge to 256 and then randomly cropping to a square shape of \( 224 \times 224 \). Data augmentation via regular horizontal flips is also used.

For the temporal domain, the number of unsupervised chunks has been fixed to 4. From each of them, 6 consecutive frames are randomly extracted resulting in a total of 24 non-uniformly sampled frames along the video sequence.

In this submission, due to computational limitations, we have just performed a prospective study, using for training only a subset of 3600 from the 28,561 training sequences (i.e. a 12.60\%)\(^2\). Final results on the whole set of test sequences defined in the challenge are highly biased by this issue.

To minimize the loss function in Equation 3 and optimize the network’s trainable parameters, the regular Stochastic-Gradient-Descent with Momentum (SGD) algorithm is used. In all our experiments the initial learning rate was set to 0.1, Momentum was set to 0.9 and weight decay was set to 0.0001. Learning rate was decayed every 200 epochs by \( 1e^{-1} \). Finally, batch size was set to 32 video sequences.

3.1.2 Inference

Following common practice, given a test sequence and its 4 chunks, we uniformly sample 5 clips for each chunk along its temporal axis. For each clip, we scale the shorter spatial side to 256 pixels and take 5 crops of \( 224 \times 224 \) to cover the spatial dimension. This results in 25 different views per chunk and so, 100 views per test sequence. We average the softmax scores for the final prediction.

We report action, verb and noun prediction probabilities for the challenge as explained in Section 2.4.

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\(^2\)The specific training subset used for the study is available at: EPIC Kitchens 2020 Subset
3.2. Main Results

As stated in Section 3.1.1, due to computational limitations we use a subset of the training set for training and validation purposes. Specifically, from the 28,561 available sequences, we selected 4500. An 80% of these sequences were dedicated for training while the rest was used for validation. These division leads to 3600 training sequences which represents a 12.60% of the available training data. Given this fact, the following prospective study is a preliminary set of experimental results which may validate our starting hypothesis. Future work will extend and complete this work by using all the available training data.

3.2.1 Preliminary Experiments

The aim of this section is to gauge the influence of the ego-motion compensation approach and the designed shared CNN architecture. To this aim, we have used the original Temporal branch architecture from SlowFast [4] as a baseline. This CNN is fed by non-compensated temporal windows of 24 consecutive frames from EPIC Kitchens sequences. To present a fair comparison with the proposed approach, training and inference details from Section 3.1 are applied in the same manner to the baseline. Results are presented in Table 1.

Comparing results obtained by the baseline (non-compensated videos, fixed temporal window) with the proposed Ours method (compensated videos, non-uniform temporal sampling) we observe an increase in performance. This preliminary experiment suggests that the use of compensated sequences along with the non-overlapping sampling, while implemented via a highly improvable approach, increases Top@1 results by a 1.25%, a 2.12% and a 1.89% for action, verb and noun respectively.

3.2.2 2020 Challenge Results

Although results are highly biased due to the reduced amount of used training data, we report 2020 Challenge results for both Seen (S1) and Unseen (S2) tests sets in Tables 2 and Table 3 respectively.

4. Conclusions

This participation describes a novel approach for action recognition in egocentric videos based on camera motion compensation and a non-uniform temporal sampling. To this aim, ego-motion is estimated for a given video sequence. To overcome the problems of motion compensation in sequences with high camera motion, each video sequence is partitioned into temporal chunks using unsupervised clustering. Camera motion is compensated for each chunk independently leading to subsequences with a quasi-static background. Compensated chunks are then fed to a shared CNN to obtain features from each of them. Late fusion gathers features from all the chunk expanding the temporal receptive field of the CNN.

We have performed a prospective study on a limited set of training data from the whole EPIC Kitchens Dataset. Preliminary results indicate that the proposed approach, while implemented in a highly improvable way, increases performance with respect to a baseline based on non-compensated sequences and a fixed temporal window of analysis.

Future work will continue exploring this line of research besides of using the whole training set available.

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