A LEARNING-BASED FRAME POOLING MODEL FOR EVENT DETECTION

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ABSTRACT
Detecting complex events in a large video collection crawled from video websites is a challenging task. When applying directly good image-based feature representation, e.g., HOG, SIFT, to videos, we have to face the problem of how to pool multiple frame feature representations into one feature representation. In this paper, we propose a novel learning-based frame pooling method. We formulate the pooling weight learning as an optimization problem and thus our method can automatically learn the best pooling weight configuration for each specific event category. Experimental results conducted on TRECVID MED 2011 reveal that our method outperforms the commonly used average pooling and max pooling strategies on both high-level and low-level 2D image features.

Index Terms— event detection, feature pooling, alternative optimization

1. INTRODUCTION
Complex event detection aims to detect events, such as “marriage proposal”, “renovating a home”, in a large video collection crawled from video websites, like Youtube. This technique can be extensively applied to Internet video retrieval, content-based video analysis and machine intelligence fields and thus has recently attracted much research attention[1, 2, 3, 4, 5]. Nevertheless, the complex event detection encounters lots of challenges, mostly because events are usually more complicated and undefinable, possessing great intra-class variations and variable video durations, as compared with traditional concept analysis in constrained video clips, e.g., action recognition. These factors make this technique far from being applicable to practical use with robust performance.

A large number of methods have been proposed to handle this challenging task[6, 7, 8, 9]. Generally speaking, the video representation is one of the most important components. For many techniques to extract the video representation, namely feature descriptors, have to be carefully designed or selected for good detection performance. Different from images, video clips can be treated as spatial-temporal 3D cuboids. Lots of spatial-temporal oriented feature descriptors have been proposed and been proved effective, such as HOG3D[10], MoSIFT[11], 3DSIFT[12] and the state-of-the-art improved Dense Trajectory(IDT)[13]. Although these spatial-temporal descriptors can intrinsically describe videos, the 2D image descriptors are still very important for describing videos in the complex event detection community due to two aspects. On one hand, compared with 2D image descriptors, the spatial-temporal feature descriptors usually require larger data storage and higher computational complexity to be extracted and processed. This problem becomes more serious for large scale datasets. On the other hand, the TRECVID Multimedia Event Detection (MED) evaluation track[14] of each year, held by NIST, reveals that combining kinds of feature descriptors, including 2D and 3D features, usually outperforms those of using a single feature descriptor[15].

Profiting from the research development in image representations, a number of good handcrafted features, including low-level ones of such HOG[16], SIFT[17], and high-level features of such Object-bank[18] along with the recently most successful Convolutional Neural Network(CNN) feature[19] can be directly applied to describe the video. The commonly-used strategy is to extract the feature representation for each frame or selected key frame of the video (we will use frame hereinafter) and then pool all feature representations into one representation with average pooling or max pooling[20]. While the max pooling just uses the maximum response of all frames for each feature component, the average pooling uses their average value. It is hard to say which one of two pooling strategies is better. Sometimes, average pooling is better than max pooling and vice versa. The performance heavily depends on the practical application or datasets. The actual strategy is manually choosing the better one through experiments conducted on validation set. Therefore, intuitively, here comes two questions: 1) can we automatically choose the better one between the two previous pooling strategies? 2) is there any pooling method superior to these two strategies?

To answer these two questions mentioned above, we propose a novel learning-based frame pooling method. We no-
tice that when human beings observe different events, they usually have different attention on various frames, i.e., the pooling weight for a particular event is inconsistent with the others. This phenomenon inspires us to adaptively learn the optimal pooling way from data. In other words, our approach can automatically derive the best pooling weight configuration for each specific event category. To this end, we design an alternative search strategy, which embeds the optimization process for frame pooling weight and classifier parameters into an unifying optimization problem. In this way, for a given test video clip and its pre-processed frame-level feature matrix, our optimum pooling parameters can represent a given test video clip and its pre-processed frame-level features into an unifying optimization problem. In this way, for each specific event category. To this end, we design can automatically derive the best pooling weight configuration for a particular event is inconsistent with the others. Here $m$ is the dimension of the feature in each frame. First, we construct a Lagrange interpolation function $\tilde{f}_{i,j}(u)$ for the $j^{th}$ feature component as following:

$$
\tilde{f}_{i,j}(u) = \sum_{t=1}^{T_i} \prod_{k=t-1}^{t-1} (u-k) \prod_{k=t+1}^{T_i} (u-k) y_{i,j}(t),
$$

where $\tilde{f}_{i,j}(u)$ can fit all the responses at each time (frame) $u$ in the original video clip. With the interpolated functions for all feature components, we can re-sample a fixed number of the feature representations. Thus, the videos with various durations are eventually able to re-normalized into ones with the same number $T$ of feature representations. However, we would encounter the “over-fitting” problem if directly conducting interpolating operation on the original encoded features. This is due to the fact that the original feature components may varies greatly even between consecutive frames and hence will cause the corresponding interpolation function to vary dramatically in the feature space. This would produce potential noise data. For the sake of alleviating this problem, we sort independently all features for each component in descent order before constructing the Lagrange interpolation function. In this way, the interpolation function will tend to gradual decreasing in the feature space, we denote it as $f_{i,j}(u)$. Later, we sample along the temporal axis for the $j^{th}$ feature component with $f_{i,j}(u)$, denoted as $\pi_{i,j}$:

$$
\pi_{i,j} = \{ f_{i,j}(t_k^i) \}, \quad k \in \{1, 2, 3, \ldots, T\},
$$

where $t_k^i = 1 + (k-1) \frac{T_i - 1}{T-1}$, are the re-sampling points on the interpolated function. For a given video clip, we combine all sampled feature vectors together into a new feature matrix, denoted as $X_i = (\pi_{i,1}, \pi_{i,2}, \pi_{i,3}, \ldots, \pi_{i,m})^T \in \mathbb{R}^{m \times T}$.

2.2. Formulation

Given $n$ training samples $(X_i, y_i)(i = 1, 2, \ldots, n)$, where the $X_i$ is the feature matrix obtained by Section 2.1 and $y_i$ is the sample label, our goal is to learn a weight parameter to compress the feature matrix $X_i$ into a single feature vector. Actually, for both average and max pooling methods, the pooling operation is done independently for each feature component. Intuitively, we should learn an independent
weight vector $\theta_j (j = 1, \cdots, m)$ for each component. However, this would make the model too complex to be learned effectively. Instead, we learn a single weight vector $\theta$ for all components. Namely, we pool the features using the same weight vector for all feature components as $X_i\theta$. Because our interpolation function $f_{i,j}$ will perform a decreasing property in feature space, we can easily know that the cases of $\theta = (1/T, \cdots, 1/T)$ and $\theta = (0, 0, \cdots, 0)$ approximately correspond to average and max pooling strategies, respectively. Furthermore, the medium and min pooling strategies can also be approximately viewed as the specific cases, where $\theta = (0, \cdots, 1, \cdots, 0)(1 \text{ is located in the middle position of the vector})$ and $\theta = (0, 0, \cdots, 1)$, respectively. Nevertheless, our goal is to learn an optimal pooling strategy for each event.

To this end, the problem of pooling parameter $\theta$ learning is formulated as the following optimization problem:

$$
\min_{w, b, \theta} \sum_{i=1}^{n} \left(1 - y_i (w^T X_i + b)\right)_+ + \frac{1}{2} w^T w,
$$

subject to $\theta \geq 0$, $\sum_{k=1}^{T} \theta_k = 1$,

where $(\cdot)_+ = \max(0, \cdot)$ means the hinge-loss in the loss function. Our model intends to minimize the objective function over $w, b$, which are the parameters of the hyperplane in the SVM classifier, along with our additional pooling parameter $\theta$.

### 2.3. Solution

In order to solve the parameters of $w, b, \theta$ in the model \((3)\) above, an alternative search strategy is employed. In general, our alternative search strategy can be viewed as an iteration approach with two steps in each round. The first step in each iteration is to update $w, b$ with fixed $\theta$ by solving the following sub-optimization problem:

$$
(w, b) = \arg \min_{w, b} \sum_{i=1}^{n} \left(1 - y_i (w^T X_i + b)\right)_+ + \frac{1}{2} w^T w.
$$

Here, we initialize $\theta$ with random values with constraint that $\theta \geq 0$, $\sum_{k=1}^{T} \theta_k = 1$. Equation \((4)\) is the standard formulation of a linear SVM problem and therefore can be solved via off-the-shelf tools like libsvm\([21]\).

The second step in an iteration is to search $\theta$ by fixing the $w, b$ obtained by the first step. This step actually iteratively updates an optimal pooling manner under current model parameter $w, b$:

$$
\theta = \arg \min_{\theta} \sum_{i=1}^{n} \left(1 - y_i (w^T X_i + b)\right)_+.
$$

Because the operation between $X_i$ and $\theta$ is a linear inner product, the second step in one iteration can also be solved via Gradient Descent algorithm. In this degree, the overall objective function can be minimized with expected convergence by iteratively searching for $w, b$ and $\theta$, respectively. The overall algorithm is illustrated in Algorithm \([1]\).

**Algorithm 1** Alternative search strategy to obtain optimum $w, b, \theta$

**Input:** $X_i, y_i$ (the training set feature matrices and labels),

**Output:** learned parameter $w, b, \theta$

1. Initialize $\theta$ with random values, s.t. $\theta \geq 0$, $\sum_{j=1}^{T} \theta_j = 1$;

2. for $k:=1$ to $N$ 

   a) Fixing $\theta$ and updating $w, b$:

   $$(w_k, b_k) = \arg \min_{w, b} \sum_{i=1}^{n} \left(1 - y_i (w^T X_i + b)\right)_+ + \frac{1}{2} w^T w;
   \quad \text{end for}

   \quad$$

3. Return $w_N, b_N$ and $\theta_N$;

### 3. EXPERIMENTS

We evaluate our proposed model on the public large scale TRECVID MED2011 dataset\([14]\) with both low-level features: HOG, SIFT, and high-level features: Object Bank-based feature and CNN-based feature. We adopt the most popular pooling methods of the max and average poolings as the baseline methods for comparison.

#### 3.1. Dataset and evaluation metric

The TRECVID MED 2011 development set is used to assess our method. It contains more than 13,000 video clips over 18 different kinds of events and background class, which provides us with real life web video instances consisting of complex events under different scenes lasting from a few seconds to several minutes. We follow the original evaluation metric along with the pre-defined training/test splits of MED 2011 development set. In the pre-processing stage, we empirically interpolate each video clips into $T = 20$ frames. Besides, each learning-based frame pooling model for individual event class is trained with 100 times of iteration, which enables the objective function to be minimized to convergence. Finally, the average precision(AP) value is used to evaluate different pooling approaches.
3.2. Results on low-level features

We use the off-the-shelf toolkit VLFeat to extract HOG and SIFT features with standard configurations for each frame. It is worth noting that the SIFT descriptors are densely extracted. Then the Bag-of-Words method is employed to encode the raw features from each frame into a 100 dimensional vector. The results are listed in Table 1.

| Event ID | HOG  | SIFT |
|----------|------|------|
| E001     | 0.407| 0.345|
| E002     | 0.302| 0.369|
| E003     | 0.527| 0.586|
| E004     | 0.279| 0.307|
| E005     | 0.185| 0.217|
| E006     | 0.179| 0.175|
| E007     | 0.083| 0.112|
| E008     | 0.162| 0.269|
| E009     | 0.327| 0.357|
| E010     | 0.151| 0.136|
| E011     | 0.082| 0.080|
| E012     | 0.107| 0.144|
| E013     | 0.110| 0.126|
| E014     | 0.192| 0.177|
| E015     | 0.097| 0.104|
| P001     | 0.123| 0.162|
| P002     | 0.350| 0.379|
| P003     | 0.057| 0.066|
| mAP      | 0.207| 0.226|

Table 1. The AP comparison among average pooling, max pooling and our optimal pooling method for low-level features on TRECVID MED11 dataset.

From Table 1, it can be obviously observed that our method is effective on most events for both HOG and SIFT features. For the HOG descriptor, our model leads to apparent AP improvements on 14 out of 18 events, and our learning-based method outperforms the max and average pooling strategies by 0.026 and 0.045 in mAP, respectively. As to the SIFT descriptor, the APs of overall 13 out of 18 events are improved by our method and our method outperforms the max and average pooling strategies by 0.008 and 0.018 in mAP, respectively. It is worth noting that it is very hard to improve mAP, even by 0.01 since the TRECVID MED11 is a very challenging dataset.

3.3. Results on high-level features

We test two kinds of high-level features: CNN-based feature and Object Bank-based feature. When it comes to the CNN-based feature, we directly employ the vgg-m-128 network, pre-trained on ILSVRC2012 dataset, to extract feature on each single frame. In detail, we use the 128 dimensional fully connected layer feature as the final feature descriptor, denoted as “CNN 128d”. The Object Bank-based descriptor is a combination of several independent “object concept” filter responses, where We pre-train 1,000 Object filters on the ImageNet dataset. For each video frame, we employ the maximum response value for each filter as the average max and average pooling strategies by 0.026 and 0.045 in mAP, respectively. As to our method has an improvement of around 0.02 in mAP compared with average and max pooling methods. Averagely, our method has an improvement of around 0.02 in mAP compared to baseline methods for object bank-based feature, while around 0.002 in mAP for CNN-based feature.

From Table 1 and 2, we can see that it is hard to determine which one of the baseline methods is better. Their performances rely heavily on the feature descriptors and event types. In contrast, our method performs the best in most cases (and in average).

4. CONCLUSION

In this paper, we propose a learning-based frame pooling model to address the complex event detection task. Compared with commonly used average pooling and max pooling approaches, our method can automatically derive the pooling weight among frames for each event category. Experimental results conducted on TRECVID MED 2011 dataset reveal that our approach is more effective and robust for both low-level and high-level image descriptors compared with traditional pooling methods.

5. REFERENCES

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