Multiple Instance-Based Video Anomaly Detection using Deep Temporal Encoding-Decoding

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Abstract. In this paper, we propose a weakly supervised deep temporal encoding-decoding solution for anomaly detection in surveillance videos using multiple instance learning. The proposed approach uses both abnormal and normal video clips during the training phase which is developed in the multiple instance framework where we treat video as a bag and video clips as instances in the bag. Our main contribution lies in the proposed novel approach to consider temporal relations between video instances. We deal with video instances (clips) as a sequential visual data rather than independent instances. We employ a deep temporal and encoder network that is designed to capture spatial-temporal evolution of video instances over time. We also propose a new loss function that is smoother than similar loss functions recently presented in the computer vision literature, and therefore; enjoys faster convergence and improved tolerance to local minima during the training phase. The proposed temporal encoding-decoding approach with modified loss is benchmarked against the state-of-the-art in simulation studies. The results show that the proposed method performs similar to or better than the state-of-the-art solutions for anomaly detection in video surveillance applications.

Keywords: anomaly detection, surveillance videos, weakly supervised multiple instance learning

1 Introduction

Video anomaly detection is defined as the process of detecting the occurrence of "abnormal" events in video clips that differ from previously defined "normal" clips. Automatic detection of anomalies in video has gained an increased attention in the past few years [1,15,24,32,36]. This is mainly due to the difficulty of manual processing (requires extensive manpower) of the abundant visual information generated by surveillance cameras. From security perspective, the detection of events such as stealing, fighting and shoplifting is of the interest. Examples of such activities are shown in Figure 1.

Unsupervised anomaly detections are commonly formulated for rare event de-
Fig. 1. Different normal and abnormal examples for different surveillance videos taken from UCF-crime dataset [38]. (A): Vandalism; (B): Stealing; (C): Shoplifting; (D): Shooting; (E): Robbery; (F): Road Accident; (G): Robbery; (H): Fighting; (K): Assault; (L): Arson; (M): Arrest; (N): Abuse; (O): Normal scene 1; (P): Normal scene 2; (Q): Normal scene 3.

tection which has been studied as an outlier detection problem where normality model is trained using normal videos and any deviation from this model is considered as an anomaly.

Unsupervised anomaly detection is usually performed either by using handcrafted features followed by feature learning or via development of an end-to-end deep network. The earlier approaches for anomaly detection commonly involved extraction of trajectory features to make use of its ability to describe the dynamics of moving objects [8,35]. In addition, different spatial-temporal handcrafted features such as color, texture and optical flow have been used for anomaly detection [13,25,30]. However, due to illumination change, scale and deformation, these features do not generalize well for large scale video analysis. Therefore, unsupervised deep learning has been used for feature extraction and model learning [1].

The aforementioned methods are based on normality deviation. However, Chandola et al. [10] showed that it is ambiguous to define a boundary between normal and abnormal, mostly due to the definition of normal events that can take into account all possible normal patterns or behaviors. Therefore, the use of both normal and abnormal events for learning has been studied in [38] using a weakly supervised method. The main reason for formalizing the problem within weakly supervision is due to the lack of temporal labeling of abnormal videos. Sultani et al. [38] propose to tackle this within the multiple instance learning framework where the bag (video) label is available and a model is trained to infer the instance label. They employed multiple instance hinge loss function and designed a network that processes video clips (independently from each other).
In this paper, we propose a new solution that hierarchically captures low, intermediate and high level temporal and spatial information. The contribution of this work is two-fold: (i) we propose a novel solution for anomaly detection in videos that uses a temporal encoding network to capture the temporal and spatial information of video instances, and (ii) the formulation of this solution is implemented within the weakly supervised multiple instance framework where we propose a loss function that is smoother than its counterpart and outperforms the state-of-the-art.

2 Background

In this section, a brief review of the most recent works on video-based anomaly detection methods is presented. Generally, the common approach for visual anomaly detection is based on extracting handcrafted or deep representation features, and model learning. In this approach, anomaly detection is usually formulated as an outlier detection problem.

Tracking-based anomaly detection methods were the earlier approaches used for dynamic feature extraction to model the normal pattern of movements of objects of the interest [35]. In [41], anomaly detection based on semantic scene trajectory clustering was proposed. In this method, first blob detection is performed to detect the object of interest. Then feature extraction is performed using spatial and velocity information. These features are then clustered based on their similarities (in term of the size of the object and their velocity) and the result is used to form trajectory. Hu et al. [21] proposed an anomaly detection using trajectory clustering of motion pattern. First, foreground pixels are detected using background subtraction method, then the features are clustered using the Fuzzy K-mean clustering algorithm. Anomaly detection is then carried out by comparing the learned motion pattern probability distribution obtained from the trajectories. In general, tracking-based methods are not robust enough for complex video scene analysis since they involve different complex steps such as object detection, data association and tracking, and any failure in these steps causes a failure in the anomaly detection system.

Due to the limitation of tracking-based methods, handcrafted spatial-temporal features have been employed to model the motion pattern for anomaly detection. The most straightforward approach is to extract low-level appearance features and motion cues such as color, texture and optical flow [13,30,25,23,32], and use them to model motion activity patterns. In [32], social force model combined with optical flow features is used to learn normal pattern for global motion and any deviation from this model (with low probability) is considered an anomaly. In [44], Spatial Temporal Interest Point (STIP) detector was used to detect the region of interest and then Histogram of Gradient (HOG) as an appearance feature descriptor and Histogram of Optical Flow (HOF) as motion feature descriptor were used to detect abnormal activity in videos. In [31], spatial and temporal anomaly detection in crowded scene are tackled by jointly modeling mixture of appearance and dynamics. Spatial anomalies are detected using dis-
criminant saliency, while; temporal anomalies are detected as an event with low probability.

Recently, unsupervised deep learning using auto-encoder network has been widely used for latent features representation and anomaly detection. Hasan et al. [20] used the reconstruction error of the fully connected convolution autoencoder as an anomaly score. In [42], a rich and descriptive motion and appearance feature representation using a stacked autoencoder is proposed. Anomaly detection is performed based on anomaly score calculated using multiple one class SVM on the learned feature representation.

Abate et al. [1] tackled the anomaly detection problem by utilizing the ability of the network on remembering the normal events and evaluating the degree of network surprisal. The remembering aspect of the network is modeled by the reconstruction error of the autoencoder. Also, the surprisal aspect of the network is modeled by calculating the density of latent features using the autoregressive network. During the training phase, the joint loss function that combines negative log of the reconstruction error and probability density of latent features is used. The novelty of this work lies in modelling the probability density of the latent features using autoregressive model. Most of the autoencoder-based networks are based on element-wise measures such as the squared error. However, the problem of the element-wise metric is its poor performance in modeling the properties of human visual perception. For instance, a small image translation might cause large pixel-wise error [26].

The majority of solutions developed for anomaly detection in video are based on unsupervised learning where only normal videos are used for learning and anomaly detection is detected as an outlier detection problem (low probability, anomaly score and reconstruction error). Most video anomaly datasets used for the training and testing are short scenes and cannot generalize to all possible normal pattern. As a result, it is very hard to build a boundary between normal and abnormal events due to the lack of videos that model all possible normal patterns [10]. Therefore, Sultani et al. [38] introduced a new approach based on weak supervision where both normal and abnormal videos are used for anomaly detection. In their solution, the anomaly detection problem is formulated within the Multiple Instance Learning (MIL) framework where only bag label is available. In this work, the video is divided into a fixed number of instances (clips) and a multi layer perceptron network is trained to predict instances labels based on deep ranking approach [38].

The above network deals with instances (clips) independently and does not capture low, intermediate and long temporal information which are very importance for video data analysis. Sequence modeling has been used in different fields such as language modeling [33], video summarization [37] and action segmentation [17] to capture the temporal information.

Inspired by the success of temporal convolution in the sequence modelling, we propose a temporal encoding network for anomaly detection in surveillance videos. The proposed network aims to capture the temporal information between video instances. In addition, the problem is also tackled within the MIL frame-
work (weakly supervised) and we formulate a smooth loss function that is robust to video scene variations and encourage to its global optimal.

3 Methodology

The proposed solution is shown in Figure 2. First, we extract the video spatial-temporal features using C3D network [40]. Then, these features are divided into a fixed number of non-overlapped clips. These clips form sequential instances in the bag. The proposed temporal encoding-decoding network finds how normal/abnormal features instances evolve over time. During the training phase, we use both normal and abnormal videos using our a deep ranking loss function to update the network weights.

![Diagram](image)

**Fig. 2.** Proposed approach of temporal-encoding decoding network. Normal and abnormal videos are fed into C3D [40] network to extract spatial-temporal features then these features are divided into 32 clips to form instances. These instances are treated as sequential visual information by our network, the temporal encoding decoding captures how these features evolve over time and predict its anomaly score then using our mapping from instance to label using our loss function.

3.1 Temporal Encoding-Decoding Network

Before introducing the network structure, we define the sequence modeling task. In the sequence modeling, we assume that we have an input sequence as $x_0, \ldots, x_T$ where $x_i \in \mathbb{R}^d$ where $d$ is the input features vector and at each time step we want to predict the corresponding output $y_0, \ldots, y_T$. Formally, we can define
the sequence modeling network as a mapping function \( f : \mathcal{X}^{T+1} \rightarrow \mathcal{Y}^{T+1} \) as follows [5]:

\[
\hat{y}_0, \ldots, \hat{y}_T = f(\hat{x}_0, \ldots, \hat{x}_T).
\]  

(1)

Note that the number of time steps \( T \) is not fixed and depends on the number of sequences of the problem. The goal of learning in sequence modeling is to build a network \( f \) that minimizes a loss function between actual output and the predicted ones, \( \mathcal{L}(y_0, \ldots, y_T, f(\hat{x}_0, \ldots, \hat{x})) \). Recurrent Neural Network (RNN) is the commonly used network architecture for sequence modeling [18]. Recent works have shown that 1-D convolution can be also employed for different tasks that involve sequence modeling such as audio synthesis [33], machine translation [14] and action segmentation [27]. Therefore, we have employed 1D temporal convolution for our network. One of the applications of sequence modeling is autoregressive prediction (predict the signal value given its past, where no future information to be used).

Temporal Convolutional Network (TCN) is a network which inherits the properties of convolutional neural networks and use them to sequential learning. TCN is a causal network where there is no information leakage from the future to the past [5]. Commonly, TCN consists of 1D fully convolutional network (FCN) and causal convolution in which zero padding of length (kernel size-1) is added to keep the length of the hidden layer the same as the input layer [5].

Inspired by [27], we proposed a modified TCN network, shown in Figure 3. The new TCN network consists of a temporal encoder/decoder. Our proposed encoder/decoder network consists of two steps, each step has 1D temporal convolutional layer, a temporal pooling/upsampling layer, and channel-wise normalization layer. In particular, layer \( L \) in the encoder/decoder network contains a set of 1D temporal filters, parameterized by tensor \( W_l \in \mathbb{R}^{F_l \times C_d \times F_l-1} \) where \( l \in \{1, \ldots, L\} \) is the layer index and \( C_d \) is the temporal convolution duration length and \( F_l \) is the number of convolution filters. These filters are designed to capture the spatial-temporal features and their evolution over the time from one clip to another. The activation function \( \hat{E}^{(l)}_{i,t} \) for the \( i \)th component \( (i = \{1, \ldots, F_l\}) \), of the \( l \) layer is defined as:

\[
\hat{E}^{(l)}_{i,t} = f(b^l_i + \sum_{t'=1}^{C_d} < W^l_{i,t',} E^{(l-1)}_{0,t+C_d-t'>}),
\]  

(2)

where \( E^{(l-1)} \) is the normalized activation from previous layer, \( f(\cdot) \) is the Leaky Rectified Liner Unit, \( b \in \mathbb{R}^{F_l} \) are bias vectors and \( < \cdot, \cdot > \) is the regular convolution operation. The channel-wise normalization is done as follows [27]:

\[
E^{(l)} = 1/(m + \epsilon) \hat{E}^{(l)},
\]  

(3)

where \( \max_i \hat{E}^{(i,l)} \) is the highest response at time step \( t \) and \( \epsilon = 1 \times 10^{-5} \) is very small number. Max-pooling with width equal \( T_l = 1/2T_{l-1} \) is done across the temporal domain for each encoder layer.
The decoder architecture is similar to the encoder with the exception of the max-pooling layer which is replayed by the upsampling layer. The last layer of the decoder is a sigmoid layer, which calculates the anomaly score with the temporal domain. The training is performed within a weakly supervised framework using normal and abnormal videos, note that the temporal annotation of abnormal videos is not provided. As a result, the loss function is formulated within the multiple instance learning framework and explained in the following section.

**Fig. 3.** The proposed network, temporal encoding-decoding network. The number besides each color coded layer reflects the number of convolution filters used in our network. The script $T$ represents the number of instance in temporal domain.

### 3.2 Multiple Instance Deep Ranking

In a multiple instance learning (MIL) context, the task is to learn a classifier based on a set of bags where each bag contains multiple instances. In the MIL settings, the label of the bag is available during the training. However, the labels for the instances are not provided. Existing MIL methods can be classified into bag paradigm and instance paradigm [9]. In the bag paradigm, the aim is to predict the label of the bag, whereas, in the instance paradigm, the aim is to predict the instance label [34]. Commonly, the main assumption of the MIL is that the bag is positive if at least one instance is positive (for example it is anomaly) and the bag is negative if all instances in the bag are negative. This assumption is used to map the label from the instance level to the bag level. However, in the most applications such as image segmentation or a fine-grained
sentiment classification, it is crucial to find the instance label given only bag label during training (weakly supervised).

Recently, there is an increased interest within the computer vision community to study weak supervised applications, specially within the MIL framework such as object detection and localization [6,12], image classification [7], and video-based anomaly detection [38]. This is due to the fact that MIL relaxes the need for instances label (the temporal annotation in our case) and only bag label (video label) is needed. In the following sections, we review MIL deep ranking and related works.

Mathematical Formulation of MIL Deep Ranking

Let $X \in \mathcal{X}$ be the instance-level input random variable and $Y_X \subset \mathcal{Y}_X$ is the instance output, where the space of $X$ is $\mathcal{X} \subset \mathbb{R}^d$, and $d$ is the dimension of the feature vector, also, $\mathcal{Y}_X = \{0, 1\}$. Assume $B \in \mathcal{B}$ is the bag-level input random variables and $Y_B \in \mathcal{Y}_B$ is the bag-level output. For instance-based binary classification problem where the training samples is i.i.d, the binary classifier can be defined as follows:

$$ f(x) = \text{sign}(g(x)) \in \{+1, -1\}, $$

where $g(\cdot)$ is a mapping function $g : \mathbb{R}^d \rightarrow \mathbb{R}$. For the support vector machine (SVM), the optimization problem is reduced to a quadratic program problem [39]:

$$ \min_{\alpha \in \mathbb{R}^d, \beta \in \mathbb{R}} \frac{1}{2}||\alpha||^2 + C \sum_{i=1}^N \max \{0, 1 - y_i (\alpha^T \phi(x_i) + \beta)\}, $$

where $C > 0$ is a penalty parameter, $\beta \in \mathbb{R}$ is a bias parameter, $\alpha \in \mathbb{R}^m$ is the $m$-dimensional classifier weight to be learned, $x_i \in \mathbb{R}^d$ is the $d$-dimensional instance feature vector, $\phi : \mathbb{R}^d : \mathbb{R}^m$ and $y_i$ is the label of the instance. The first term of (5) is the $L_2$ regularization and the second term is the hinge loss term, defined as $g(x) = \max(0, 1 - x)$. It is important to mention that the hinge loss function is not differentiable [43]. Therefore, different algorithms have been proposed as a solution, such as using the numerical approximation of the hinge loss [29] or using the generalized hinge loss [3]. The maximum margin classifier SVM formulation has been extended to the MIL. In this case, the goal of SVM is to infer the bag label from the instances using the maximum score of the instances in the bag [4]:

$$ \min_{\alpha \in \mathbb{R}^d, \beta \in \mathbb{R}} \frac{1}{2}||\alpha||^2 + C \sum_{j=1}^{N_B} \max_{i \in B_j} \{0, 1 - Y_{B_j}(\max(\alpha^T \phi(x_i) + \beta))\}, $$

where $N_B$ is the total number of the bags. Sultani et al. [38] reformulate the MIL ranking problem into a rank regression problem. The main assumption is
that the anomalous bags should always have a higher anomaly score compared to the normal bags:

$$\max_{i \in B_a} f(B^i_a) > \max_{i \in B_n} f(B^i_n), \quad (7)$$

where max is taken over video instances, $B_a$ and $B_n$ are the abnormal and normal video bags, and $f(B_a)$ and $f(B_n)$ are the predicted abnormal and normal anomaly scores, respectively. The first term of Eq. (7) represents the segment that has the highest anomaly score in abnormal video, which is more likely to be anomalous instance. However, the second term of Eq. (7) represents the video segment with the highest anomaly score for normal video which is a normal instance. The loss equation, $\mathcal{L}(\cdot)$, proposed in [38] includes temporal smoothness of the abnormal video segments as well as sparsity term:

$$\mathcal{L}(B_a, B_n) = \max(0, 1 - \max_{i \in B_a} f(B^i_a) + \max_{i \in B_n} f(B^i_n)) + \lambda_1 \sum_{i=1}^{n=32} (f(B^i_a) - f(B^{i+1}_a))^2 + \lambda_2 \sum_{i=1}^{n=32} f(B^i_n), \quad (8)$$

where $\lambda_1$ and $\lambda_2$ are hyper-parameters that control the amount of trade-off and $n$ is the number of instances in the video bag. The second term of equation [8] is the $L_2$ regularization smoothness term which ensures that the anomaly score of abnormal video should vary smoothly between video segments. The third term of equation [8] is the $L_1$ regularization sparse which reflects the fact that anomaly in abnormal videos occurs for a short time only. It is evident that the first term of the loss function penalizes the positive bags with low scores.

The problem of the aforementioned loss function is based on the assumption that the bag label is inferred from the maximum score of the instances in the bag, $Y_B = \max(f(x_i))$. The problem arises from the fact that the max function is not smooth [22] and the optimization suffers from the vanishing gradients [23]. To alleviate this problem, we propose to use the average difference between normal and abnormal bags in our loss function instead of the max operation:

$$\mathcal{L}(B_a, B_n) = \left[ 1 - \left\{ \max_{i} \frac{\sum_{i=1}^{n=32} f(B^i_a)}{n} - \frac{\sum_{i=1}^{n=32} f(B^i_n)}{n} \right\} \right] + \lambda_1 \sum_{i=1}^{n} f(B^i_a), \quad (9)$$

This formulation will take into account not only the one instance with the maximum score but also the scores of all instances in the bag. In addition, the defined loss function maximizes the distance between the normal instance scores and abnormal instance scores. The proposed loss function has only one max operation involved which makes it more smooth than that of the one proposed in [8]. To penalize the loss function of the abnormal bag, similar to [8], we added $L_1$ regularization term.
4 Experiments

In this section, we test our proposed temporal encoding-decoding network with the proposed loss function using UCF-cirme dataset [38]. We also compare the proposed solution with the state-of-the-art approaches. In addition, qualitative and quantitative analysis are carried out.

4.1 Datasets

In this paper, the UCF-crime dataset [38] have been used which a large scale dataset of long videos with different scenes that represent real-life situations. The dataset consists of 1900 videos divided into training sets and testing sets. The training sets consist of 800 normal videos and 810 abnormal videos and the test sets include 150 normal and 140 abnormal videos (290 videos in total). The abnormal videos in both training and testing cover 13 real-world anomalies with following descriptions: Abuse, Arrest, Arson, Assault, Accident, Burglary, Explosion, Fighting, Robbery, Shooting, Stealing, Shoplifting and Vandalism, see Figure 1. The total dataset duration is 128 hours. In this dataset, no temporal (frame-level) annotation is available except for the testing videos. The UCF-crime dataset is the biggest video anomaly dataset and the only one that has multiple scenes with real surveillance videos. Please refer to [38] for more details.

4.2 Implementation Details

Feature Extraction and Bag Generation First, pre-processing operations is performed before feeding it into the C3D network. Each video frame is resized into 240 × 320 with frame rate fixed to 30 fps. We followed the same technical procedure in [38] to extract the C3D features. We extracted the spatial-temporal features from the fully connected layer (FC6) of the C3D network [40]. The C3D network computes the C3D features for every 16 frames and then followed by $l_2$ normalization. We divide each video to 32 non-overlapping clips and each clip is treated as an instance in the video bag. Since we deal with a fixed number of instances per bag, the video instance feature (clip) is generated by taking the average for all 16-frame clip features within that video clip. During the training, a random selection of 30 normal videos and 30 abnormal videos is carried out and then feed it as mini-batch to the proposed network as shown in Figure 2.

Proposed Network Implementation The proposed work is implemented using Keras [11] backend with Theano (http://deeplearning.net/software/theano/) and python. We set the temporal convolution kernel length to 4 and different kernel lengths is tested and reported. The number of convolution filters used in our network is set to {512, 32}, respectively. The last layer of our network is the temporal fully connected layer with a sigmoid activation. We use $l_2$ regularizer for kernel weight parameters for each layer. We used dropout to prevent overfitting. Adaptive subgradient optimizer [16] is used to update network parameters with learning rate set 0.01. The $\lambda_1$ in our loss function is set to $8 \times 10^{-5}$. 
4.3 Metrics

Similar to [38, 24], we used the frame level-based receiver characteristic (ROC) and area under the curve (AUC) metrics to evaluate the proposed method. These metrics are calculated using frame-level ground truth annotation of the test videos. Please note that we do not use equal error rate (EER) as it does not measure anomaly correctly as reported in [38, 28].

4.4 Experimental Results

We compared our proposed method with the baseline method [38] as well as methods discussed in [20, 30]. The proposed method by Lu et al. [30] used a dictionary-based approach to learn the normal pattern from the normal videos and used the reconstruction error as the anomaly score. Hassan et al. [20] used deep auto-encoder using normal videos to learn normal features representation and used reconstruction error as an anomaly scores.

The quantitative comparisons in terms of ROC and the AUC is reported in Figure 4 and Table 1. From Figure 4 it is observed that using normal and abnormal videos in the training phase increases the true positive rate as shown in both Sultani et al. [38] (red plot) and our proposed method (green plot). In addition, it is evident that our proposed approach has a higher true positive rate compared to other methods. Table 1 shows that our network with the modified loss function achieves the state-of-the-art results for video anomaly detection. We also show that training our network with Sultani et al. loss achieve higher results compared to their network because our network exploits the temporal relation between video instances.

Qualitative results on eight different videos that show success and failure cases are reported in Figure 5. The first row shows that our method produces a high anomaly score for abnormal videos (explosion and fighting) in a timely manner and generates near-zero anomaly score for normal videos which means that our method generate a low false alarm. We believe that the reason for generating an early anomaly score (first and second col.) is due to the temporal convolution over the instances which proves that our method produces an early detection. The second row shows the cases that our method fails in producing correct anomaly score for different abnormal videos and normal video.

False Alarm Rate  Similar to [38], the false alarm rate on normal testing videos is analysed. The reason for this study is due to the fact that most of the surveillance videos are normal and generating a high false alarm rate is not practical. Therefore, a robust anomaly detection method should report a low false alarm rate on normal videos. We evaluated the performance of our proposed method on normal testing videos and we list the false alarm rate at 50% threshold for different methods as shown in Table 2. It is clear that our proposed method has generated a very low false alarm rate in comparison to the based-line method and other methods which proves the effectiveness of the proposed methods.
Fig. 4. ROC comparative results for different methods, binary classifier (blue), Lu et al. [30] (cyan), Hassan et al. [20] (black), Sultani et al. [38] (red), and our proposed method (green).

Fig. 5. Qualitative results of our method on testing videos. The first row shows an example of success cases and the second row shows an example of failure cases where our method can not produce correct anomaly score.
Study the Effect of Temporal Convolution Kernel Size

In this section, we show the effect of different convolution kernel sizes on the performance of the proposed approach. Figure 6 shows the AUC with different convolution lengths. The experimental results show that temporal convolution with kernel size set to 4 has the highest AUC performance compared to other setups.

Ablative Experiments

In this section, we show how our network architecture is different from the network ED-TCN [27]. First of all, we want to empathize that the network in [27] has been used for semantic segmentation and to accom-
modate the ED-TCN network to our problem, we have changed the last layer to sigmoid instead of softmax. In addition, we have changed the number of filters in each layer. This is the first time temporal encoding and decoding is used within a weakly supervised approach. Also, we have used our loss function and similar parameter settings mention earlier. **Note that**, for fair comparison we set the convolution kernel-size to four for all cases. Table 3 shows that using the same network with our proposed loss function achieve only $AUC=76.56$ and using our loss with our network settings increase the AUC to 79.49.

Table 3. AUC comparison results for different network settings and different temporal networks.

| Method                                      | AUC  |
|---------------------------------------------|------|
| Our loss+ Lea et al. [27] network settings  | 76.56|
| Sultani et al. loss+ Lea et al. [27] network settings | 78.89|
| Our loss+ Bi-LSTM [19] network              | 50.12|
| **Proposed (our loss+ our network)**        | **79.49**|

5 Conclusion

We propose a deep temporal encoding-decoding network for anomaly detection in video surveillance applications. Our proposed solution is based on the deep ranking multiple instance learning where we used normal and abnormal videos during the training to localize the anomaly event in real surveillance videos. We deal with video instances (clips) as sequential visual data and build a temporal encoding network that exploits the low, intermediate, high-level spatial-temporal evolution between these feature instances. Due to the lack of temporal annotation of visual video instances we use the average sum of the instance predication to pool from the instance-level to bag-level predication. Therefore, our loss function is smoother than using max-pooling in previous work. Experimental results show that using normal and abnormal videos achieves better results compared to using only normal videos and we achieve the state-of-the-art result on the UCF-crime dataset.

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