A VIDEO ANOMALY DETECTION FRAMEWORK BASED ON APPEARANCE-MOTION SEMANTICS REPRESENTATION CONSISTENCY

Xiangyu Huang¹, Caidan Zhao¹∗, and Zhiqiang Wu²

¹ School of Informatics, Xiamen University
² PKU-Wuhan Institute for Artificial Intelligence

ABSTRACT

Video anomaly detection is an essential but challenging task. The prevalent methods mainly investigate the reconstruction difference between normal and abnormal patterns but ignore the semantics consistency between appearance and motion information of behavior patterns, making the results highly dependent on the local context of frame sequences and lacking the understanding of behavior semantics. To address this issue, we propose a framework of Appearance-Motion Semantics Representation Consistency that uses the gap of appearance and motion semantic representation consistency between normal and abnormal data. The two-stream structure is designed to encode the appearance and motion information representation of normal samples, and a novel consistency loss is proposed to enhance the consistency of feature semantics so that anomalies with low consistency can be identified. Moreover, the lower consistency features of anomalies can be used to deteriorate the quality of the predicted frame, which makes anomalies easier to spot. Experimental results demonstrate the effectiveness of the proposed method.

Index Terms—video anomaly detection, prediction, two-stream AutoEncoder, feature fusion

1. INTRODUCTION

Video anomaly detection (VAD) refers to identifying events that do not conform to expected behavior [1], which is of great practical value in public safety scenarios. In addition to much effort devoted in [2, 3], VAD remains an extremely challenging task due to the rarity and ambiguity of anomalies [1]. It is infeasible to collect balanced normal and abnormal samples and tackle this task with a supervised binary classification model. Therefore, a typical solution to VAD is often formulated as an unsupervised learning problem, where the goal is to train a model by using only normal data to mine regular patterns. The events that do not conform to this model are viewed as anomalies.

∗Corresponding Author. This work was supported in part by the National Natural Science Foundation of China under Grant No. 61971368, No. U20A20162 and No. 61731012, and in part by the Natural Science Foundation of Fujian Province of China No. 2019J01003.
work’s performance. Furthermore, Liu et al. [8] use a hybrid framework in a combination of flow reconstruction and frame prediction, but the result is highly dependent on the quality of flow reconstruction in the previous phase, which makes it difficult to train a stable model. Moreover, the correlations modeled by these methods are essentially designed for recovering the pixel information but still lack the understanding of behavior semantics.

In this paper, we take a step forward in making full use of the multi-modal knowledge from normal events to detect anomalies via a simple yet novel network based on Appearance-Motion Semantics Representation Consistency, termed AMSRC-Net. Specifically, inspired by SOTA methods that use multiple modalities [8, 10, 12, 14], we first extract the representative features of appearance and motion in normal events by a universal two-stream encoder. Unlike previous works, we observe the consistency between the features of two modalities and propose a novel consistency loss to model the semantics consistency in the feature space explicitly. Then, the proposed network generates lower consistent features for abnormal samples, which typically reflect irregular behavior semantics and can be used to detect anomalies. Moreover, we design a simple flow-guided fusion module, which utilizes the above feature semantics consistency gap to augment the prediction quality gap. Extensive experiments on three public VAD datasets show that our proposed AMSRC-Net achieves better performance than SOTA methods.

2. PROPOSED METHOD

As shown in Figure 1, our proposed AMSRC-Net consists of three parts: A two-stream encoder, a decoder, and a flow-guided fusion module (FGFM). We first input the previous video frame image and its optical flow clip into the two-stream encoder to get the appearance and motion’s feature representations. Then the proposed consistency loss is used to enhance further the consistency of the feature semantics between appearance and motion information in normal samples. Next, two consistent modality features are put into the flow-guided fusion module. Finally, feeding the fused feature into the decoder to predict the future frame image. The detailed network architecture of AMSRC-Net is shown in Figure 2 and all the components are presented in the following subsections in detail.

**Two-stream Encoder and Decoder.** The two-stream encoder extracts feature representations from input video frame images and the corresponding optical flows. Due to the consistency constraints, the extracted features’ semantics are highly similar, representing the foreground behavior properties in the surveillance video. Then the decoder is trained to generate the next frame by taking the aggregated feature formed by fusing the extracted features from the previous step. The aggregated feature may lack low-level information, such as backgrounds, textures, and so on. To solve this problem, we add a UNet-like skip connection structure [15] between the frame stream encoder and decoder to preserve these low-level features irrelevant to behavior for predicting the high-quality future frame. **FGFM.** Since ReLU activation is adopted at the end of the two-stream encoder, many feature representations have zero value in the output features. During the training for the semantics consistency of two-stream features, we observe that the distribution of two-stream features over non-zero feature representations is highly consistent. In contrast, the lower consistency of appearance-motion features generated by abnormal data reflects a larger difference in the distribution of two-stream features over non-zero feature representations. In order to utilize the above feature representation gap to improve the VAD performance, we design a simple flow-guided fusion module to enlarge the prediction error gap between normal and abnormal samples. Given appearance features $\text{fea}_{\text{frame}}$ and motion features $\text{fea}_{\text{flow}}$, we use Hadamard product between the activation of $\text{fea}_{\text{frame}}$ and $\text{fea}_{\text{flow}}$ without the linear projection and residual operation to produce the fused feature $\text{fea}_{\text{fused}}$, which is used for prediction:

$$\text{fea}_{\text{fused}} = \text{fea}_{\text{frame}} \odot (\sigma (\text{fea}_{\text{frame}}) \odot \text{fea}_{\text{flow}})$$  \hspace{1cm} (1)$$

where $\sigma$ denotes Sigmoid function, $\odot$ and $\oplus$ denote Matrix Addition and Hadamard product, respectively. There is a gap in the fused feature representation between normal and abnormal data, and only the fused feature of normal data is trained to generate a high-quality future frame. With the increase of the gap in the fused feature representation during training, the gap in the quality of the predicted frame is also enlarged.

**Loss Function.** We follow the previous VAD work based on prediction [3], using intensity and gradient difference to make the prediction close to its ground truth. The intensity loss guarantees the similarity of pixels between the prediction and its ground truth, and the gradient loss can sharpen the predicted images. We minimize the $\ell_2$ distance between the predicted frame $\hat{x}$ and its ground truth $x$ as follows:

$$L_{\text{int}} = \| \hat{x} - x \|^2_2$$  \hspace{1cm} (2)$$

The gradient loss is defined as follows:

$$L_{\text{gd}} = \sum_{i,j} \| \hat{x}_{i,j} - x_{i-1,j} - x_{i,j} - x_{i-1,j} \|_1$$

$$+ \| \hat{x}_{i,j} - x_{i,j-1} - x_{i,j} - x_{i,j-1} \|_1$$  \hspace{1cm} (3)$$

where $i, j$ denote the spatial index of a video frame.

In order to model the appearance and motion semantic representation consistency of normal samples, we minimize the cosine distance between the appearance and motion features of normal samples encoded by the two-stream encoder. The proposed consistency loss is defined as follows:

$$L_{\text{sim}} = 1 - \frac{\langle \text{fea}_{\text{frame}}, \text{fea}_{\text{flow}} \rangle}{\| \text{fea}_{\text{frame}} \|_2 \| \text{fea}_{\text{flow}} \|_2}$$  \hspace{1cm} (4)$$

Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
Then, the overall loss $L$ takes the form as follows:

$$L = \lambda_{int}L_{int} + \lambda_{gd}L_{gd} + \lambda_{sim}L_{sim} + \lambda_{model} \|W\|^2_2$$  (5)

where $\lambda_{int}$, $\lambda_{gd}$, and $\lambda_{sim}$ are balancing hyper-parameters, $W$ is the parameter of the model, and $\lambda_{model}$ is a regularization hyper-parameter that controls the model complexity.

Anomaly Detection. Our anomaly score is composed of two parts during the testing phase: the inconsistency between appearance and motion feature $S_f = 1 - \frac{\text{fea}_{\text{frame}} \cdot \text{fea}_{\text{flow}}}{\|\text{fea}_{\text{frame}}\| \|\text{fea}_{\text{flow}}\|}$ and the future frame prediction error $S_p = \|\hat{x} - x\|^2_2$. Then, we get the final anomaly score by fusing the two parts using a weighted sum strategy as follows:

$$S = w_f \frac{S_f - u_f}{\delta_f} + w_p \frac{S_p - u_p}{\delta_p}$$  (6)

where $u_f$, $\delta_f$, $u_p$, and $\delta_p$ denote the means and standard deviations of the inconsistency between appearance and motion feature and prediction error of all the normal training samples, respectively. $w_f$ and $w_p$ represent the weights of the two scores.

3. EXPERIMENTAL RESULTS

Implementation Details. We evaluate our approach on three public VAD benchmarks, including UCSD ped2 [16], CUHK Avenue [17], and ShanghaiTech [2] datasets. Following [8, 18], we train our model on the patches with foreground objects instead of the whole video frames. In advance, all foreground objects are extracted from original videos for the training and testing samples. RoI bounding boxes identify foreground objects. For each RoI, a spatial-temporal cube (STC) composed of the object in the current frame and the content in the same region of previous $t$ frames will be built, where the hyper-parameter $t$ is set to 4. And the width and height of STCs are resized to 32 pixels. The corresponding optical flows are generated by FlowNet2 [19], and the STCs for optical flows are built in a similar way. Due to the existence of many objects in a frame, we select the maximum anomaly score of all objects as the anomaly score of a frame. We adopt Adam optimizer with an initial learning rate of $2e^{-4}$, decayed by 0.8 after every ten epochs. The batch size and epoch number of Ped2, Avenue, and ShanghaiTech are set to (128, 60), (128, 40), (256, 40), $\lambda_{int}$, $\lambda_{gd}$, $\lambda_{sim}$, and $\lambda_{model}$ for Ped2, Avenue, and ShanghaiTech are set to (1, 1, 1, 1), (1, 1, 1, 1), (1, 1, 1, 1). Then the error fusing weights $w_f$, $w_p$ for Ped2, Avenue, and ShanghaiTech are set to (1, 0.01), (0.2, 0.8), (0.4, 0.6).

Evaluation Criterion. We follow the widely popular evaluation metric in video anomaly detection [3, 8, 14] and evaluate our method using the frame-level area under the ROC curve (AUC) metric. The ROC curve is measured by varying the threshold over the anomaly score. Higher AUC values represent better performance for anomaly detection.

Anomaly Detection Results. To evaluate the performance of our AMSRC-Net, anomaly detection is performed on three public benchmarks. Examples in Figure 3 show anomaly score curves of some testing video clips. The anomaly score is calculated by Equation 6 and can be utilized to detect anomalies. The red regions denote the ground truth anomaly.

| Methods          | UCSD Ped2 | CUHK Avenue | ShanghaiTech |
|------------------|-----------|-------------|--------------|
| ConvAE[4]        | 90        | 70.2        | N/A          |
| ConvLSTM-AE[5]   | 88.1      | 77          | N/A          |
| MemAE[6]         | 94.1      | 83.3        | 71.2         |
| Frame-Pred[3]    | 95.4      | 85.1        | 72.8         |
| MNAD-R[7]        | 97        | 88.5        | 70.5         |
| VEC[18]          | 97.3      | 90.2        | 74.8         |
| AMC[12]          | 96.2      | 86.9        | N/A          |
| AnoPCN[13]       | 96.8      | 86.2        | 73.6         |
| AMMC-Net[14]     | 96.6      | 86.6        | 73.7         |
| HP²-VAD[8]       | 99.3      | 91.1        | 76.2         |
| AMSRC-Net        | 99.5      | 93.8        | 76.6         |

Fig. 2. Detailed network architecture of AMSRC-Net.

dis matriz

Table 1. AUROC (%) comparison between the proposed AMSRC-Net and state-of-the-art VAD methods on three public benchmarks.

Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
To our best knowledge, we compare our AMSRC-Net with several SOTA methods, and the results are summarized in Table 1. It is evident that AMSRC-Net outperforms SOTA methods on all three benchmarks. In particular, we note that the proposed method achieves 93.8% frame-level AUROC on CUHK Avenue, which is the best performance achieved on Avenue currently and exceeds the SOTA performance by 2.7%.

**Ablation Studies.** We perform corresponding ablation studies to analyze the impact of different components of AMSRC-Net, including optical flow (motion) stream, consistency loss, and FGFM. The results are showed in Table 2. We can see that the introduction of optical flow brings a trivial improvement (A vs. B). After the establishment of semantic consistency between appearance and motion, the performance is significantly enhanced (B vs. D), showing the vital correlation between the two modalities for VAD is captured. Furthermore, the FGFM significantly enhances the AUC score by 1.3% based on semantic consistency (D vs. E), proving the effectiveness of our idea.

To show that our proposed FGFM can enlarge the gap in the quality of the predicted frame between normal and abnormal data, the visualized results of representative normal/abnormal events are demonstrated in Figure 4. As we can see, the FGFM can help to produce larger differences for abnormal events, and these differences are observed in regions with motion behavior semantics. Such observations imply that AMSRC-Net pays more attention to high-level behavior semantics for anomalies.

![Fig. 3. Anomaly score curves of some testing video clips. Red regions represent ground truth anomalous frames.](image)

| Table 2. Ablation studies of each component in our AMSRC-Net on the CUHK Avenue dataset. |
|---|---|---|---|---|
| Index | Optical Flow | Semantic Consistency | FGFM | AUC (%) |
| A | × | × | × | 90.6 |
| B | ✓ | × | × | 90.8 |
| C | ✓ | ✓ | × | 91.2 |
| D | ✓ | ✓ | ✓ | 92.5 |
| E | ✓ | ✓ | ✓ | 93.8 |

![Fig. 4. Visualization examples of the ground truth frames (Target), completed frames by AMSRC (AMSRC Output), completed frames by AMSRC without FGFM (AMSRC w/o FGFM Output), completion errors by AMSRC (AMSRC Error), and completion errors by AMSRC without FGFM (AMSRC w/o FGFM Error).](image)

**4. CONCLUSION**

This paper presents a framework of Appearance-Motion Semantics Representation Consistency that uses the gap of appearance and motion semantic representation consistency between normal and abnormal data to detect anomalies. We design a two-stream encoder to extract normal samples’ appearance and motion features and add constraints to strengthen their consistent semantics so that abnormal ones with lower consistency can be identified. Moreover, the lower consistency of appearance and motion features of anomalies can be fused by the flow-guided fusion module to affect the quality of predicted frames, making anomalies produce larger prediction differences. Experimental results on three public benchmarks show that our method performs better than state-of-the-art approaches.
5. REFERENCES

[1] Varun Chandola, Arindam Banerjee, and Vipin Kumar, “Anomaly detection: A survey,” ACM Computing Surveys (CSUR), vol. 41, no. 3, pp. 1–58, 2009.

[2] Weixin Luo, Wen Liu, and Shenghua Gao, “A revisit of sparse coding based anomaly detection in stacked rnn framework,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 341–349.

[3] Wen Liu, Weixin Luo, Dongze Lian, and Shenghua Gao, “Future frame prediction for anomaly detection–a new baseline,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 6536–6545.

[4] Mahmudul Hasan, Jonghyun Choi, Jan Neumann, Amit K Roy-Chowdhury, and Larry S Davis, “Learning temporal regularity in video sequences,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 733–742.

[5] Weixin Luo, Wen Liu, and Shenghua Gao, “Remembering history with convolutional lstm for anomaly detection,” in 2017 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2017, pp. 439–444.

[6] Dong Gong, Lingqiao Liu, Vuong Le, Budhaditya Saha, Moussa Reda Mansour, Svetha Venkatesh, and Anton van den Hengel, “Memorizing normality to detect anomaly: Memory-augmented deep autoencoder for unsupervised anomaly detection,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1705–1714.

[7] Hyunjong Park, Jongyoun Noh, and Bumsub Ham, “Learning memory-guided normality for anomaly detection,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 14372–14381.

[8] Zhan Liu, Yongwei Nie, Chengjiang Long, Qing Zhang, and Guqing Li, “A hybrid video anomaly detection framework via memory-augmented flow reconstruction and flow-guided frame prediction,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 13588–13597.

[9] Dan Xu, Yan Yan, Elisa Ricci, and Nicu Sebe, “Detecting anomalous events in videos by learning deep representations of appearance and motion,” Computer Vision and Image Understanding, vol. 156, pp. 117–127, 2017.

[10] Shiyang Yan, Jeremy S Smith, Wenjin Lu, and Bailing Zhang, “Abnormal event detection from videos using a two-stream recurrent variational autoencoder,” IEEE Transactions on Cognitive and Developmental Systems, vol. 12, no. 1, pp. 30–42, 2018.

[11] Hung Vu, Tu Dinh Nguyen, Trung Le, Wei Luo, and Dinh Phung, “Robust anomaly detection in videos using multilevel representations,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, vol. 33, pp. 5216–5223.

[12] Trong-Nguyen Nguyen and Jean Meunier, “Anomaly detection in video sequence with appearance-motion correspondence,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1273–1283.

[13] Muchao Ye, Xiaojiang Peng, Weihao Gan, Wei Wu, and Yu Qiao, “Anopcn: Video anomaly detection via deep predictive coding network,” in Proceedings of the 27th ACM International Conference on Multimedia, 2019, pp. 1805–1813.

[14] Ruichu Cai, Hao Zhang, Wen Liu, Shenghua Gao, and Zhifeng Hao, “Appearance-motion memory consistency network for video anomaly detection,” in Proceedings of Conference on Artificial Intelligence, 2021, pp. 938–946.

[15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2015, pp. 234–241.

[16] Vijay Mahadevan, Weixin Li, Viral Bhalodia, and Nuno Vasconcelos, “Anomaly detection in crowded scenes,” in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE, 2010, pp. 1975–1981.

[17] Cewu Lu, Jianping Shi, and Jiaya Jia, “Abnormal event detection at 150 fps in matlab,” in Proceedings of the IEEE International Conference on Computer Vision, 2013, pp. 2720–2727.

[18] Guang Yu, Siqi Wang, Zhiping Cai, En Zhu, Chuanfu Xu, Jianping Yin, and Marius Kloft, “Cloze test helps: Effective video anomaly detection via learning to complete video events,” in Proceedings of the 28th ACM International Conference on Multimedia, 2020, pp. 583–591.

[19] Eddy Ilg, Nikolaus Mayer, Tonmoy Saikia, Margret Keuper, Alexey Dosovitskiy, and Thomas Brox, “Flownet 2.0: Evolution of optical flow estimation with deep networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2462–2470.