

#### Hochschule Bonn-Rhein-Sieg University of Applied Sciences

# Survey on Video-based Anticipation for Anomaly Detection

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### Introduction

- Anticipation: obtaining future outcomes based on past observations
- Anomaly detection: detecting deviations comparing nominal and observed

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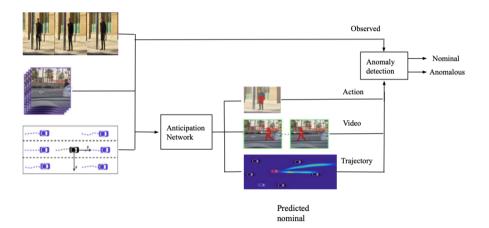


Figure 1: Block diagram of anticipation



#### Introduction

#### **Objectives**

- Anticipation methods for anomaly detection
- Identify approaches applied to detect anomalies
- Compare different types of anticipation

#### **Methods**

- Feedforward: Convolutional Neural Network (CNN) [Zhao et al., 2017]
- Recurrent model: Long-Short Term Memory (LSTM) [Sadegh Aliakbarian et al., 2017]
- Generative model: Generative Adversarial Network (GAN) [Kwon and Park, 2019]

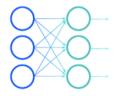


Figure 2: Feedforward architecture

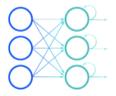


Figure 3: Recurrent model

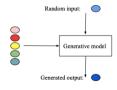


Figure 4: Generative model

## **Survey topics**

- Action anticipation
- Video prediction
- Trajectory prediction
- Anomaly detection



## Action anticipation: feedforward architecture

Prediction in one shot: shorter processing time

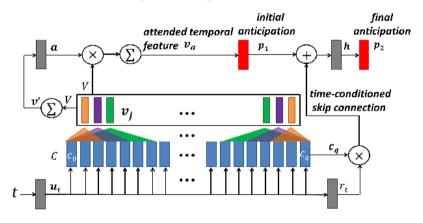


Figure 5: Architecture of time-conditioned action anticipation [Ke et al., 2019]



## **Action anticipation**

Feedforward architectures: greater accuracy for long predictions

Method	Advantages	Disadvantages
Feedforward archi-	Short and long term antici-	Application specific
tecture	pation	
Recurrent models	Early anticipation, high	Less prediction accuracy for
	accuracy for shorter se-	longer sequences
	quences	
Generative models	Long term, realistic predic-	Less accuracy
	tions	

Table 1: Summary of action anticipation



## Video prediction: generative model

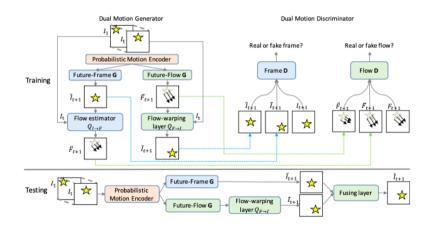




Figure 6: Dual GAN architecture for video prediction [Liang et al., 2017]

## **Video prediction**

Generative models: high quality predictions

Method	Advantages	Disadvantages
Feedforward archi-	Long-term prediction	Blurry prediction, not suit-
tecture		able for real-world scenar-
		ios
Recurrent models	Long-term clear predictions	High computational cost
Generative models	High quality frame prediction	Not suitable for real-world complex scenarios

Table 2: Summary of video prediction

## **Trajectory prediction: recurrent model**

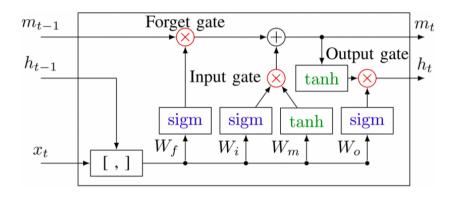


Figure 7: LSTM internal structure for trajectory prediction [Altché and de La Fortelle, 2017]

## **Trajectory Prediction**

Recurrent models: long-term predictions, complex scenarios

Method	Advantages	Disadvantages
Feedforward archi-	Immediate, realistic predic-	Fails for real-world applica-
tecture	tions	tions
Recurrent models	Long-term prediction, complex scenarios	Delayed prediction
Generative models	Long-term, accurate predictions	Not suitable for complex scenarios

Table 3: Summary of trajectory prediction

## **Summary**

Type of anticipation	Method	Application
Action anticipation	Feedforward architectures	Long and short-term prediction
	Recurrent models	Early action anticipation
	Generative models	Long-term realistic predictions
Video prediction	Feedforward architectures	Long and short-term prediction
	Recurrent models	Long-term prediction
	Generative models	Accurate predictions
Trajectory prediction	Feedforward architectures	Immediate prediction
	Recurrent models	Long-term crowded scenarios
	Generative models	Accurate long-term predictions

Table 4: Summary of methods used for anticipation



# **Anticipation for anomaly detection**

- Network is trained only based on nominal data
- In testing phase, network is provided with a new set of values
- Output from network: normal/anomalous event
- Reconstruction error [Chandola et al., 2009]

$$\delta_i = \frac{1}{n} \sum_{j=1}^{n} (x_{ij} - o_{ij})^2 \tag{1}$$

#### **Autoencoder**

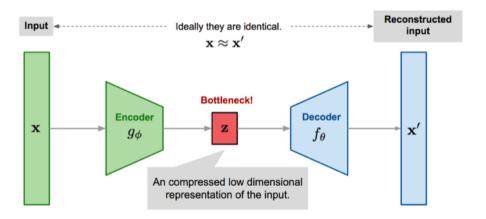


Figure 8: Basic architecture of autoencoder [Ulger et al., 2021]



#### **Conclusions**

- Long-term predictions: feedforward architectures, generative models
- Early long-term predictions: recurrent models: less accuracy
- Accurate long-term anticipations
  - Recurrent models + feedforward architectures
  - Recurrent models + generative models
- Anticipation along with anomaly detection
  - GAN
  - Autoencoders
  - Autoencoder-based



#### **Contributions**

- Categorization of anticipation
- Highlighted best method for each anticipation
- Recommended best approach for anticipation along with anomaly detection

# Thank You



#### References

- F. Altché and A. de La Fortelle. An Istm network for highway trajectory prediction. In 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pages 353–359, 2017.
- V. Chandola, A. Banerjee, and V. Kumar. Anomaly detection: A survey. ACM Comput. Surv., 41(3), July 2009. ISSN 0360-0300.
- Q. Ke, M. Fritz, and B. Schiele. Time-conditioned action anticipation in one shot. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 9925–9934, 2019.
- Y.-H. Kwon and M.-G. Park. Predicting future frames using retrospective cycle gan. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1811–1820, 2019.
- X. Liang, L. Lee, W. Dai, and E. P. Xing. Dual motion gan for future-flow embedded video prediction. In The IEEE International Conference on Computer Vision (ICCV), Oct 2017.
- M. Sadegh Aliakbarian, F. Sadat Saleh, M. Salzmann, B. Fernando, L. Petersson, and L. Andersson. Encouraging Istms to anticipate actions very early. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), Oct 2017.
- F. Ulger, S. E. Yuksel, and A. Yilmaz. Anomaly detection for solder joints using  $\beta$ -vae, 2021.
- Y. Zhao, B. Deng, C. Shen, Y. Liu, H. Lu, and X.-S. Hua. Spatio-temporal autoencoder for video anomaly detection. In Proceedings of the 25th ACM International Conference on Multimedia, page 1933–1941. Association for Computing Machinery, 2017. ISBN 9781450349062.

