Anomaly event detection based on people trajectories for surveillance videos

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Abstract

In this work, we propose a novel approach to detecting anomalous events in videos based on people movements, which are represented through time as trajectories. Given a video scenario, we collect trajectories of normal behavior using people pose estimation and employ a multi-tracking data association heuristic to smooth trajectories. We propose two distinct approaches to describe the trajectories, based on Convolutional Neural Network and Recurrent Neural Network. We use these models to describe all trajectories where anomalies are those that differ much from all normal trajectory. Experimental results show that our model is comparable with state-of-art methods and also support the idea of using trajectories to find other type of useful information, helping to understand people behavior, for instance the existence of rare trajectories.

1 Introduction

Abnormal event detection for video surveillance refers to the problem of finding patterns in sequences that do not conform to expected events [10]. It is a challenging problem because the definition of anomaly is subjective to the particular scene context, giving origin to a large number of possibilities. For instance, someone running at a marathon is a normal event, while someone running during a regular working day might be due to an emergency, an anomalous event. Therefore, the difficulty of anomaly recognition is related to the semantics that are observed in the scene.

Due to the success of Deep Neural Networks (DNN), researchers started to employ them to solve the anomaly recognition problem [12]. For instance, CNN-based approaches describe anomalies by creating models that combine optical flow and texture information from spatiotemporal regions [22]. Models that use AE or Convolutional AE (CAE) [20] aim at describing events in non-supervised fashion. Thus, anomalies are representations that differ from normal (i.e., an anomaly occurs when the AE is not able to perform a satisfactory reconstruction). Similar to AE, GAN-based approaches learn the normal behavior using a generative model [18], in which anomalies are recognized by the discriminator since the generator built an anomaly representation based in normal situations. Furthermore, RNN models usually appear accompanied with DNN, specially for movement data [6]. The idea is to combine the recurrent information of what is considered normal and create a representation of it. Nevertheless, most of these models depend on the camera position. Thus, these models learn specific patterns of the camera view which cannot be transferred to other views without retraining. Similarly to handcrafted features [9], these techniques also extract texture (appearance) and movement (flow) information. On the other hand, in our model, the source of information for anomaly representation is different. Specifically, our model extracts information from trajectories. An important difference with these models is the fact that our model is not affected by large color intensity changes.

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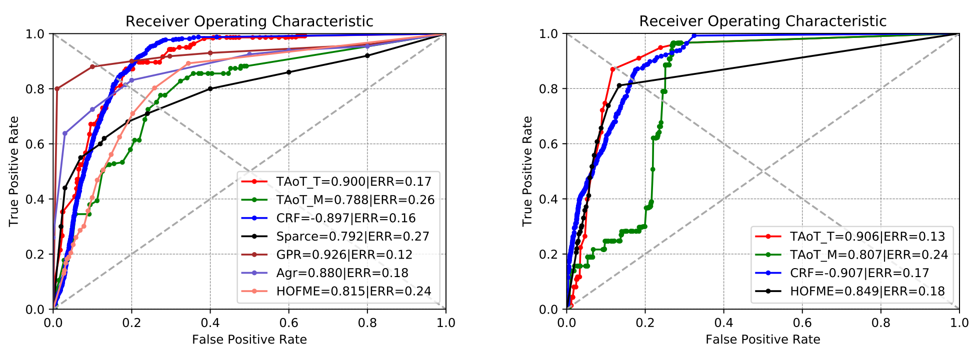
Anomaly recognition models based on trajectories [25] are among first approaches in visual anomaly recognition. The main drawback of this model was the problem of people detection and trajectory building. However, with novel approaches and technologies, this issue has been progressively reduced. The model proposed by Cosar *et al.* [8] considers trajectories to build regions which are examined in a time lapse to find texture and movement information. The process is divided into two phases: description and filtering. Li *et al.*[13] proposed a technique that describes the scene using a sparse representation of overlapping trajectories, these trajectories are grouped and abnormal events are recognized when they differs much from any cluster. While Saini *et al.* [23] used trajectories to train a Hidden Markov Model (HMM) combined with genetic algorithm to detect anomalies by their low probability,the model proposed by Zhou *et al.* [29] developed a method based on HMM and feature clustering. An important difference between these approaches and ours is that our model does not segment the trajectories in parts or blocks, it focuses in complete trajectory. Furthermore, for surveillance purposes, region based models analyze motion characteristics, which are not meaningful without accurate localization of the targets. Thus, trajectories present the complete event that contains the anomaly.

In this work, we exploit high level information to create a robust representation for anomaly recognition. Our approach models people movements by leveraging from body skeletons obtained through a state-of-the-art pose estimator. The reference points are extracted from body skeleton and aggregated through time, building a trajectory. Each trajectory is then represented using deep neural networks to better encode its morphology. Our hypothesis is that trajectories are able to encode the necessary information from movement to recognize certain anomalous events. Since our proposed approach is based on trajectories, it is more robust to the aforementioned issues that affect movement and appearance approaches, because it, an advantage from using trajectories is that the localization of the particular individual performing an anomalous event is easily retrieved. In addition, trajectories allow other applications, such as people behavior analysis. We illustrate this application by using clustering models, such that it is possible to characterize the rarity of trajectories [28]. It is important to highlight that the proposed model is oriented to scenes where people detector and tracking algorithms may offer a good representation, thus, high crowds scenes are not considered in the scope of this research.

The novelty and contributions of this work are summarized as follows. (i) A spatial and temporal trajectory descriptor for anomaly event detection based on deep neural networks, aiming at describing trajectories by their morphology. (ii) A novel approach for anomaly recognition extracted from higher level information. (iii) A heuristic for multi-object tracking for data association based on Kalman filter. (iv) An experimental evaluation regarding trajectories and the relation between anomalies and rarity.

The pipeline of our proposed approach for anomaly recognition comprising four main steps: (i) reference point estimation, (ii) tracking building, (iii) feature extraction, and (iv) anomaly and rare trajectory recognition. Figures 1(a) and 1(b) present some of our experimental results in Subway dataset [1].



(a) (b)

Figure 1: Experimental results and comparison with the state-of-the-art on the *Entrance* and *Exit* sequences. (a) ROC results for Entrance clip; (b) results for the Exit clip.

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