Chapter 24
Clustering Based on Two Layers for Abnormal Event Detection in Video Surveillance

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ABSTRACT

Abnormal event detection has attracted great research attention in video surveillance. In this paper, the authors presented a robust method of trajectories clustering for abnormal event detection. This method is based on two layers and benefits from two well-known clustering algorithms: the agglomerative hierarchical clustering and the k-means clustering. Facing to the challenges related to the trajectories, e.g., different sizes, the authors introduce a preprocessing step to unify their sizes and reduce their dimensionality. The experimental results show the performance and accuracy of their proposed method.

1. INTRODUCTION

Abnormal event detection is an active research area in video surveillance. An abnormal event is defined as a pattern in the data that does not conform to the expected normal event. The common representation of an event is the trajectory of the objects in the scene since object trajectories provide rich spatiotemporal information about an object activity (Morris & Trivedi, 2011; Sung, Feldman, & Rus, 2012). Thus, the abnormal event detection consists in abnormal trajectory detection. The core problem tackled by the various methods for abnormal event detection in the literature (Cong, Yuan, & Liu, 2013; Andersson et al., 2013) is how to define the abnormal event. Research in this area commonly follows the line that normal events are first learned from training data, and are then used to detect events deviated from

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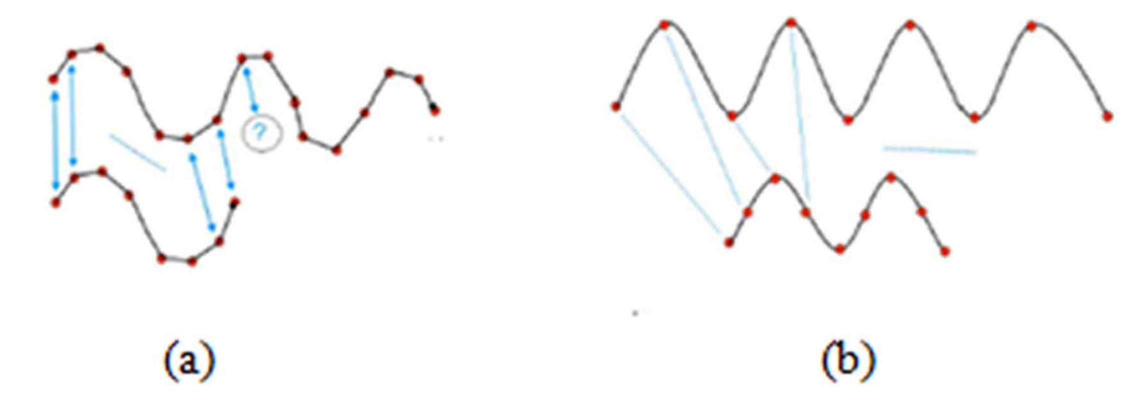
Figure 1. Some difficulties of trajectories (Porikli, 2004): a) unequal lengths, b) equal lengths but different sampling rates



this representation. Clustering-based approaches are the most widely adopted solution for this problem (Morris & Trivedi, 2011; Beyan & Fisher, 2013). Trajectory clustering is the process of grouping a set of trajectories into homogeneous groups (called clusters), where the within-group-trajectory similarity is minimized and the between-group-trajectory dissimilarity is maximized. The two important aspects, heavily related to the trajectories clustering, are: (1) a trajectory representation that is suitable for clustering, (2) a distance function that can determine whether two trajectories are similar or dissimilar. According to the trajectories' representations, the distance functions can be calculated either with raw trajectory representation (as they were already registered from the tracking) or with preprocessed trajectories that have suffered a preprocessing step. The main difficulties when dealing with trajectories are their unequal lengths, different sampling rates (leading to local time shift), noise (Porikli, 2004) and their high dimensional data (Han, Kamber, 2005) (*cf.* Figure 1). Working directly with such data in its raw format is very expensive in terms of both processing and storage cost. Preprocessing can unify the size of trajectories or offer new representations to trajectories by reducing their dimensionality/dimension, while still preserving the fundamental characteristics (Naftel & Khalid, 2006a).

In our work, we propose a new method for trajectories' clustering. Our method seeks to extract clusters of normal trajectories required to classify a new trajectory as a normal or abnormal event. The novel contributions of this paper are the following: (1) Our proposed method for trajectories' clustering is based on two layers. In the first clustering layer, we aimed to determine the number of clusters automatically using raw representation of trajectories. The second clustering layer is based on preprocessed trajectories to extract clusters of normal events. (2) Since trajectories are of different lengths and sampling rates, we proposed to include a preprocessing step to unify the size of trajectories and reduce their dimensionality. Hence, we can calculate the Euclidean distance and benefit from its advantages.

The rest of this paper is organized as follows. Section 2 provides an overview of the state of the art related to trajectories' preprocessing and clustering. In section 3, we present our proposed method. Section 4 provides our experimental results to prove the performance of our method. Finally, Section 5 concludes the paper.