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Visual abnormal behavior detection based on trajectory sparse reconstruction analysis

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ABSTRACT

Abnormal behavior detection has been one of the most important research branches in intelligent video content analysis. In this paper, we propose a novel abnormal behavior detection approach by introducing trajectory sparse reconstruction analysis (SRA). Given a video scenario, we collect trajectories of normal behaviors and extract the control point features of cubic B-spline curves to construct a normal dictionary set, which is further divided into Route sets. On the dictionary set, sparse reconstruction coefficients and residuals of a test trajectory to the Route sets can be calculated with SRA. The minimal residual is used to classify the test behavior into a normal behavior or an abnormal one. SRA is solved by L1-norm minimization, leading to that a few of dictionary samples are used when reconstructing a behavior trajectory, which guarantees that the proposed approach is valid even when the dictionary set is very small. Experimental results with comparisons show that the proposed approach improves the state-of-the-art.

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1. Introduction

Abnormal behavior detection is important to video content understanding, with applications in intelligent video surveillance [1–4] and content-based multi-media retrieval [1,5], etc. Research in abnormal detection has made great progresses in recent years, such as abnormal action detection [5,6], abnormal event detection [7–10], and abnormal crowd detection [11–15]. All these methods can be categorized into two parts, based on visual features of video stream [10–13] or based on trajectory analysis [16–24]. In recent years, trajectory analysis based methods received much attention when performing visual abnormal behavior detection [12–18,30]. Although extensively investigated, trajectory analysis is still an open research topic with challenging problems, including the trajectory length variation [19,22], the trajectory noise [20] and the limited sizes of sample sets [16,21]. Researchers are putting a lot of effort into finding more effective trajectory representation and modeling approaches.

In the early research, trajectory representations include representative sequences corresponding to motion vectors [23], motion vectors with acceleration information [24], etc. Since these representations directly extracted the object positions and velocities in video frames, they lead to variable feature length and bring difficulties to the trajectory analysis. In the later research, fixed-length vectors based on re-sampling and linear interpolation [18,25] are proposed. These vectors can deal with the problem of trajectory length variation, but the interpolation often brings in redundant and noise information. Naftel and Khalid [26] propose an efficient trajectory representation using function approximation algorithms of Least Square Polynomial, Cheybyshev Polynomial and Discrete Fourier Transform (DFT), while the representations in transformation domain increase the complexity of the representation. In Ref. [27], a more efficient trajectory representation is proposed. Haar Wavelet Coefficients and Least-squares Cubic Spline Curves Approximation (LCSCA) are adopted as parametric feature vectors. These parametric feature vectors are insensitive to the length of trajectories, providing a general tool. The performance of these representations can be optimized by selecting proper parameters. In this paper, we follow the idea of Ref. [16] to extract trajectory representation, and make a deep discussion about the selection of proper feature parameters based on quantitative experiments.

On the other hand, various methods are investigated or employed to model the trajectories on the representations. Clustering methods, such as Self-Organizing Map Neural Network [24] and hierarchical Fuzzy *K*-means clustering [25], are used to classify trajectories in an un-supervised manner and then build prototypes. Test trajectories will be classified by their distances to the prototypes. The used distances include Euclidean distance [17], Hausdorff distance [19] or Dynamic Time Warping (DTW) [22,28] etc. The disadvantages of these distances lie in that they cannot reflect the statistical nature of behaviors. In other words, classification based on distance measurement does not consider the different importance of features as a probabilistic or discriminative method. In recent years, supervised learning methods, such as Gaussian Mixture Models (GMMs) [16], Bayesian Model [12,21], Hidden Markov Model (HMM) [29], One-Class Support Vector Machine (OC-SVM) [7], Hierarchical Hidden Markov Model [29] and Nonparametric

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Bayesian Model [21], are employed in trajectory analysis. Given a large training set, these methods can reach a good performance. But when facing a small training set, the performance of these methods cannot always be guaranteed. It is known that labeling trajectory samples in video sequences always result in huge workload due to the large amount of video data. Therefore, exploring trajectory analysis approach for a small sample set is significant.

Inspired by the development of sparse reconstruction in face recognition [31] and object tracking [32], we cast the trajectory classification as a sparse reconstruction problem. Intuition behind the sparse reconstruction lies in the fact that the coefficients imply the discriminative information (some coefficients that can compactly express the trajectory are nonzero and the others are almost zero) among different trajectory patterns, which can be used for classification. Sparse Reconstruction Analysis (SRA), solved by L1-norm minimization, is suitable to represent and reconstruct a behavior trajectory with a few of dictionary samples. In theory, given an input test sample$y \in \Re^m$, we reconstruct it by a sparse linear combination of an over-complete normal basis set$\Phi = \Re^{m \times D}$, where $m \ll D$. Therefore, this method is proposed to quantify the normalness of trajectory via a sparse reconstruction from normal ones. The reconstruction for a special behavior trajectory based on all behavior trajectories is typically sparse. According to the sparse theory [31,34,35], once sparseness is guaranteed, the size of sample set has a little effect on classification performance. This guarantees the classification performance of SRA with a small sample set, which is the main advantage of this work compared with state-of-the-art methods represented by Ref. [16], where a large sample set is required to build the models.

The rest of the paper is organized as follows. In Section 2, we introduce the trajectory representation and the abnormal behavior detection approach, in Section 3, we present the experiments with comparisons, and in Section 4 we conclude the paper with the discussion of the future work.

2. Methodology

In this section, we first present an overview of the proposed abnormal behavior detection approach and then describe the trajectory representation and the sparse reconstruction analysis.

2.1. Overview of the proposed approach

In this paper, based on a predefined trajectory dictionary set for a fixed video scenario, we propose a novel abnormal behavior detection approach using sparse reconstruction analysis. We first collect a set of trajectories of normal behaviors from videos by an object tracking algorithm [32] or a motion detection method [14,29]. By observing their appearances, these trajectories are manually categorized into different sub-sets, called Route sets. For all the collected trajectories, the Least-squares Cubic Spline Curves Approximation (LCSCA) features are extracted for representations and then construction of the dictionary set.

When performing abnormal behavior detection, each test trajectory will also be represented with LCSCA features. Then, we introduce the sparse reconstruction analysis on the normal dictionary set to classify the testing motion trajectories of objects, where our objective is to reconstruct the test trajectory with as few dictionary samples as we can. The L1-norm minimization is used to solve the reconstruction coefficients, on which the reconstruction residuals of each Route set can also be calculated. The minimal reconstruction residual is used to classify the test trajectory into a norm behavior or an abnormal one with an empirically defined threshold. The framework of the proposed approach is shown in Fig. 1.

2.2. Trajectory representation

Since motion trajectories consist of coordinate sequences of different length and are extracted on different frame numbers, we use the control points of LCSCA to extract fixed-length parametric vectors as feature representation. This is achieved by approximating each spatial-temporal trajectory with a uniform cubic B-spline curve [33] parameterized by time (frame number). Cubic B-spline curve [33] can be thought of a method for defining a sequence to approximate the form of trajectory. A spline curve is a sequence of curve segments that are connected together to form a single continuous curve (here trajectory). Further mathematical explanation is shown in the Ref. [33]. Because of the number of control points and weight factors, the representation of the basis is flexible for simple or complicated shape of curves. Given a trajectory sequence in (x, y, t) space, we use B-spline control points to represent both the shape and spatio-temporal profiles of a trajectory $T = \{(x_1,y_1),(x_2,y_2),\cdots,(x_{t-1},y_{t-1}),(x_t,y_t)\}$ in a parametric way $F = \{C_1^X,C_2^X,\cdots,C_p^X,C_1^Y,C_2^Y,\cdots C_p^Y\}$, where p is the number of control points and t is the length of trajectory [16], $C_p^X$is the normalized x coordinate of pth control point, and $C_p^Y$is the normalized y coordinate of pth control point. Fig. 2 shows a normal and an abnormal trajectories, respectively.

The transformation procedure of the trajectory representation is as follows:

(1) Define the parameter vector$s = \{0,s_2,\cdots s_{t-1},s_t\}$,

$$s_n = \frac{\sum_{i=2}^{n}\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{\sum_{i=2}^{t}\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}} \; (n = 2,3,\cdots,t, s_n \in (0,1]) \tag{1}$$

where $\sum_{i=2}^{n}\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$is the total distance traversed at a given point (x_n,y_n); and define the knot vector

$$\tau = \left\{ \underbrace{0,0,0,0,}_{1\cdots 4}\underbrace{\frac{1}{p-3},\frac{2}{p-3},\cdots,\frac{p-4}{p-3}}_{5\cdots p},\underbrace{1,1,1,1,}_{p+1\cdots p+4} \right\} \tag{2}$$

where τ denotes a knot vector with $p+4$ elements.

(2) Calculate the cubic B-spline basis function with the following recursive formulation according to De-Boor algorithm [33]

$$B_{p,1}(s_n) = \begin{cases} 1 & \text{if } \tau_p \le s_n < \tau_{p+1} \\ 0 & \text{otherwise} \end{cases},$$

$$B_{p,m}(s_n) = \frac{s_n - \tau_p}{\tau_{p+m-1} - \tau_p} B_{p,m-1}(s_n) + \frac{\tau_{p+m} - s_n}{\tau_{p+m} - \tau_{p+1}} B_{p+1,m-1}(s_n) \tag{3}$$

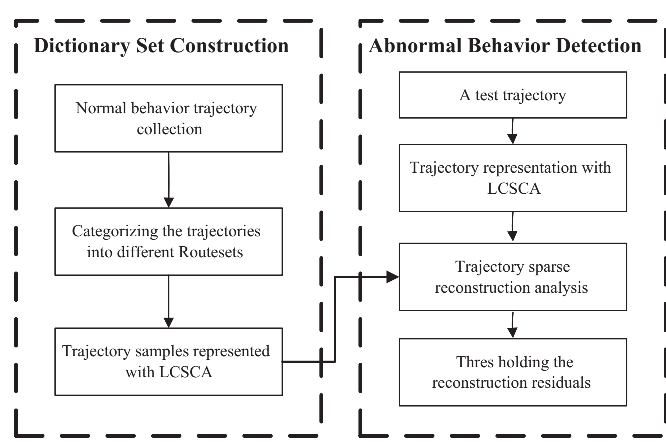

Fig. 1. Framework of the proposed approach.

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