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Local estimation of displacement density for abnormal behavior detection

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Abstract

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LOCAL ESTIMATION OF DISPLACEMENT DENSITY FOR ABNORMAL BEHAVIOR DETECTION

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ABSTRACT

Detecting abnormal behavior in video sequences has become a crucial task with the development of automatic video-surveillance systems. Here, we propose an algorithm which locally models the probability distribution of objects behavioral features. A temporal Gaussian mixture with local update is introduced to estimate the local probability distribution. The update of the feature probability distribution is thus temporal and local, allowing a smooth transition for neighboring locations. The integration of local information in the estimation provides a fast adaptation along with an efficient discrimination between normal and abnormal behavior. The proposed technique is evaluated on both synthetic and real data. Synthetic data simulates different scenarios occurring in road traffic, and illustrates how the model adapts to local conditions. Real data demonstrates the ability of the system to detect abnormal behavior due to the presence of pedestrians and animals on highways. In all tested scenarios the system identifies abnormal and normal behavior correctly.

1. INTRODUCTION

The last decade witnessed a rise in the development of abnormal behavior detection (ABD) systems due to the increasing demand in visual surveillance and security. The outcomes of ABD development are tremendous, leading to automatic and instantaneous notification of abnormal events in public places. Abnormal behavior detection is a challenging problem because it is a high-level process requiring the integration of various techniques such as feature selection, trajectory modeling, dimensionality reduction and density estimation. Moreover, most of these fields are still active areas of research; global optimal solutions are yet to be found for many problems. Abnormal behavior detection algorithms can be divided into two sub-categories: algorithms concerned with the characterization of the body posture and those concerned with the analysis of object trajectories. The algorithm proposed in this paper falls in the latter category.

Trajectory-based analysis is concerned with modeling the distribution of objects' feature vectors consisting of the object coordinates and behavioral features such as vector flow, object size, colors, etc. This combination of local and behavioral features determines whether the behavior is normal or not. ABD techniques traditionally rely upon the learning of a *global* distribution of the feature vector over the entire feature space, regardless of the nature of the feature (local or behavioral). Hidden Markov models are typically used to model the global distribution [1, 2, 3]. Neural networks have also been used for ABD with some success [4]. In particular, self organizing maps (SOMs) have attracted attention due to their ability to preserve the topology of the input data [5, 6]. Johnson and Hogg have also proposed to model the probability distribution of a feature vector composed of the position and the vector flow of the object using a competitive neural network [7] and a global Gaussian mixture model [8].

The algorithm proposed herein differs from the aforementioned techniques in that the *local* (or position) feature vector is not integrated in the distribution estimate but is rather used as a parameter to index the pdf estimate. A map of local probability distributions for the behavioral features is thus generated. The benefits are twofold: first, the dimensionality of the feature vector is reduced; second, integrating the local feature in the distribution estimate augments the rate of false detection for abnormal behavior. Indeed, global estimation of local feature is, by definition, inadequate. The paper is organized as follows. Section 2 focuses on the probability density modeling with Gaussian mixtures. In particular, subsection 2.2 introduces the concept of spatio-temporal Gaussian mixture applied to behavioral features. Subsection 2.3 is concerned with the update equations of the spatio-temporal Gaussian mixture. Section 3 presents experimental results for abnormal behavior detection using synthetic and real data, followed by the conclusion in Section 4.

2. PROBABILITY DENSITY ESTIMATION USING SPATIO-TEMPORAL GAUSSIAN MIXTURES

Trajectory-based ABD aims to estimate the distribution of the feature vector $\mathbf{X}$ over time. The problem, formulated as $P(\mathbf{X}_t|\mathbf{X}_{0:t-1})$, is often reduced to determining the probability $P(\mathbf{X}_t|\mathbf{X}_{t-1})$ where $\mathbf{X}_t$ and $\mathbf{X}_{t-1}$ are the feature vectors at times t and $t-1$, respectively, and $\mathbf{X}_{0:t-1}$ is the accumulated set of feature vectors $\{\mathbf{X}_0, \dots, \mathbf{X}_{t-1}\}$ [9, 10]. The contribution of this paper is to estimate the feature vector probability distribution characterizing an object at time t given its feature vector at time $t-1$ for a particular location. Because the probability density estimate $p(\mathbf{X}_t|\mathbf{X}_{t-1})$ is derived from local information, the coordinates of the object is not included in the feature vector $\mathbf{X}$ but is rather used to index the probability density. Let us denote by $\mathbf{S}$ the coordinates component (x, y) and φ the behavioral component (e.g. size, color, shape model, etc.) of the feature vector $\mathbf{X}$. The state of the object $\mathbf{X}$ at time t can be expressed as follows:

$$\mathbf{X}_t = \mathbf{X}_{t-1} + f_{\mathbf{S}}(\varphi), \quad (1)$$

where $f_{\mathbf{S}}(\varphi)$ is a local function of the behavioral component. Such a function is difficult to directly estimate because there is no knowledge of behaviors in the scene. Instead, we propose to approximate $f_{\mathbf{S}}(\varphi)$ by sampling from a local conditional *probability density function* (pdf):

$$p(\mathbf{X}_t|\mathbf{X}_{t-1}) \propto p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1}). \quad (2)$$

The probability density function $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$ is recursively derived from the knowledge accumulated over time.

2.1. Local Probability Density Modeling using a Gaussian Mixture

The Gaussian Mixture Model (GMM) is used to approximate the pdf $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$. It provides a continuous estimate of the density. The technique has been used in video processing for different purposes, such as motion detection [11], tracking [10, 12] or target modeling [13]. The GMM provides an estimation of the pdf by modeling the distribution with a set of Gaussian functions in order to fit the true pdf. The probability density function of a Gaussian mixture comprising K components is given by

$$p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1}) = \sum_{k=1}^K w_k g(\varphi; \mu_k, \Sigma_k), \quad (3)$$

where w_k are the prior probabilities, also called the *mixing parameters* or *weights*, and $g(\varphi; \mu_k, \Sigma_k)$ is the normal den-

sity of mean μ_k and covariance matrix Σ_k :

$$g(\varphi; \mu_k, \Sigma_k) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_k|^{\frac{1}{2}}} e^{-\frac{1}{2}(\varphi - \mu_k)^T \Sigma_k^{-1} (\varphi - \mu_k)}, \quad (4)$$

where T indicates the matrix transpose operator and n is the dimension of φ .

The GMM represented in Eq. (3) is dynamically modified to fit the probability density by updating the parameters $\{\mu_k, \Sigma_k\}$ of the closest Gaussian from the new vector φ in terms of Mahalanobis distance. In practical implementation, the Gaussian is truncated (the value is set to 0) whenever the Mahalanobis distance is greater than a given threshold τ :

$$(\varphi - \mu_k)^T \Sigma_k^{-1} (\varphi - \mu_k) \geq \tau. \quad (5)$$

If a probability is equal to 0, the corresponding Gaussian is not updated. The threshold τ thereby limits the overlapping of the tails in the representation of the probability density. Following the terminology used by Stauffer and Grimson in [14], if the probability is equal to 0, i.e. the condition in Eq. (5) holds, the vector φ does not *match* the distribution. On the other hand, if the Mahalanobis distance is below the threshold τ , the vector φ *matches* the distribution, which leads to an update of the probability distribution model. As the distribution is modeled with a constant number of Gaussians K , if the vector does not match with any of the Gaussians, a new Gaussian component is created and replaces the Gaussian with the lowest mixing weight. The Gaussian with the lowest probability of occurrence contributes the least to the density estimation as it is the least likely to match an incoming pixel; therefore, it can be removed without impairing the density drastically.

2.2. Integration of Neighborhood Information in the Gaussian Mixture Model

The Gaussian mixture model is a temporal estimation of the probability distribution. We propose here to extend the scope of the Gaussian mixture model to integrate the local context. The hypothesis underlying such an extension is that the probability distributions of neighboring locations are highly correlated. The resulting Gaussian mixture model is a temporal estimate for the local distribution. For lack of a better name, we call the estimation a spatio-temporal estimation of the probability distribution, being aware of the stretch of terminology. Let us assume that the probability density $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$ is conditioned on two, and only two, independent events at time $t-1$, e.g. two objects in motion. The first event is represented by the feature vector $\mathbf{X}_{t-1}^1$ with local feature $\mathbf{S}$, and the second event by $\mathbf{X}_{t-1}^2$ with local feature $\mathbf{S} + \delta_{\mathbf{S}}$, in the neighborhood of $\mathbf{X}_{t-1}^1$. The probability density $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$ is then given by

$$\begin{aligned}
p_S(\varphi|\mathbf{X}_{t-1}) &= p_S(\varphi|\mathbf{X}_{t-1}^1 \cup \mathbf{X}_{t-1}^2) \\
&= \frac{p_S(\varphi)}{p_S(\mathbf{X}_{t-1})} [p_S(\mathbf{X}_{t-1}^1|\varphi) + p_S(\mathbf{X}_{t-1}^2|\varphi)] \\
&= \frac{1}{p_S(\mathbf{X}_{t-1})} [p_S(\mathbf{X}_{t-1}^1)p_S(\varphi|\mathbf{X}_{t-1}^1) \\
&\quad + p_S(\mathbf{X}_{t-1}^2)p_S(\varphi|\mathbf{X}_{t-1}^2)]. \quad (6)
\end{aligned}$$

The pdf $p_S(\varphi|\mathbf{X}_{t-1}^2)$ is not known for the local feature $\mathbf{S}$ as the event $\mathbf{X}_{t-1}^2$ occurs at location $\mathbf{S} + \delta_S$, only the probability density $p_{S+\delta_S}(\varphi|\mathbf{X}_{t-1}^2)$ is. Nevertheless, the two probabilities are related by

$$p_S(\varphi|\mathbf{X}_{t-1}^2) = \xi(\delta_S)p_{S+\delta_S}(\varphi|\mathbf{X}_{t-1}^2), \quad (7)$$

where $\xi(\delta_S)$ is an unknown function. We assume ξ follows the definition of a kernel, as stated in [15], and, in particular, its value decreases with the distance from the origin. We choose the isotropic Gaussian to model the function $\xi(\delta_S)$:

$$\xi(\delta_S) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\|\delta_S\|^2/2\sigma^2}, \quad (8)$$

where $\|\cdot\|$ denotes the Euclidean norm. Knowing that there are only 2 events in the neighborhood leads to $p_S(\mathbf{X}_{t-1}) = 1$. It follows from Eqs. (3), (6) and (7) that

$$\begin{aligned}
p_S(\varphi|\mathbf{X}_{t-1}) &= \sum_{k=1}^K (w_k^1 \xi(0) g(\varphi; \mu_k^1, \Sigma_k^1) \\
&\quad + w_k^2 \xi(\delta_S) g(\varphi; \mu_k^2, \Sigma_k^2)). \quad (9)
\end{aligned}$$

Eq. 9 can be generalized to N ($N \in \mathbb{N}$) independent events. Let us denote by $l(N)$ the set of local features $\{\mathbf{S}_0, \dots, \mathbf{S}_N\}$ for the N events. The pdf $p_S(\varphi|\mathbf{X}_{t-1})$ is then given by

$$p_S(\varphi|\mathbf{X}_{t-1}) = \sum_{i=1}^N \sum_{k=1}^K w_k^i \xi(\delta_{S_i}) g(\varphi; \mu_k^i, \Sigma_k^i), \quad (10)$$

where the variables w_k^i , μ_k^i and Σ_k^i denote the weight, mean and covariance for i^{th} local feature and the k^{th} Gaussian, respectively. The weights w_k^i represent the prior probability of the Gaussian components, and hence

$$\sum_{i=1}^N \sum_{k=1}^K w_k^i = 1. \quad (11)$$

2.3. Updating the Gaussian Mixture Parameters

The probability distribution of an event is estimated through the spatio-temporal mixture of Gaussians defined in Eq. (10),

making it dependent on its neighborhood. In turn, the event is also used to update the parameters of all the distributions in a small neighborhood $\mathcal{D}$. The parameters of K Gaussians are initialized with arbitrary values since no *a priori* knowledge of the scene is assumed; in particular, the covariance matrices Σ_k are set to a multiple of the identity matrix so as to ensure the component distributions are isotropic:

$$w_k^i = w_0, \quad \mu_k^i = 0, \quad \Sigma_k^i = \sigma_0^2 I, \quad \forall i \in \mathcal{D}. \quad (12)$$

When a new event with local feature $\mathbf{S}$ occurs, the posterior probability q_k^i is calculated for each Gaussian over the neighborhood as follows:

$$q_k^i = \begin{cases} w_k^i g(\varphi; \mu_k^i, \Sigma_k^i) & \text{if } (\varphi - \mu_k^i)^T (\Sigma_k^i)^{-1} \\ & (\varphi - \mu_k^i) \geq \tau, \\ 0 & \text{otherwise.} \end{cases} \quad (13)$$

and

$$q_k^i = \frac{q_k^i}{\sum_{i \in \mathcal{D}} \sum_{k=1}^K q_k^i}. \quad (14)$$

It is important to mention that if a behavioral feature φ does not match the estimate, the posterior probabilities are not normalized and $q_k^i = 0, \forall k$. The Gaussian mixture model is adapted by updating the parameters depending on whether or not there is a match:

- If there is at least one match;

$$w_k^i = (1 - \beta \xi(\delta_{S_i})) w_k^i + \beta \xi(\delta_{S_i}) q_k^i, \quad (15)$$

$$\mu_k^i = (1 - \beta \xi(\delta_{S_i})) \mu_k^i + \beta \xi(\delta_{S_i}) \varphi, \quad (16)$$

$$\Sigma_k^i = (1 - \beta \xi(\delta_{S_i})) \Sigma_k^i + \beta \xi(\delta_{S_i}) (\varphi - \mu_k^i)^T (\varphi - \mu_k^i), \quad (17)$$

where β is a fixed learning rate ($0 < \beta < 1$).

- If there is no match;

$$w_k^i = (1 - \beta \xi(\delta_{S_i})) w_k^i, \quad (18)$$

$$l = \text{argmin}_k (w_k^i), \quad (19)$$

$$w_l^i = w_0; \quad \mu_l^i = \varphi; \quad \Sigma_l^i = \Sigma_0. \quad (20)$$

3. ABNORMAL BEHAVIOR DETECTION

The estimation of the probability density $p_S(\varphi|\mathbf{X}_{t-1})$ is used to determine whether or not a behavior represented by the behavioral feature φ is abnormal. In the proposed model, a behavior is considered elementarily abnormal if the Mahalanobis distance in Eq. (5) is greater than a given

Fig. 1. The probability density function of an object at different locations on the map: (a), (b) and (c) show the locations ($\mathbf{S}$) of the object on the map, along with possible directions of movement; (d), (e) and (f) are the respective pdf estimates $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$ using Gaussian mixtures in θ and d .

threshold τ , i.e. if there is no match between the behavioral feature and any of the Gaussian mixture's components. A trajectory is deemed abnormal if the running average of its elementary behavior is abnormal and normal otherwise. However, the results presented here will focus on elementary behavior because it allows more accurate analysis.

The Gaussian mixture model developed in Section 2 is tested for abnormal behavior detection. A truncated version $\hat{\xi}$ of the Gaussian ξ is implemented in the algorithm to reduce the computational load. The Gaussian truncated kernel $\hat{\xi}(\delta_{\mathbf{S}})$ is defined as

$$\hat{\xi}(\delta_{\mathbf{S}}) = \begin{cases} \xi(\delta_{\mathbf{S}}) & \text{if } \xi(\delta_{\mathbf{S}}) > \lambda, \\ 0 & \text{otherwise.} \end{cases} \quad (21)$$

The parameter λ is set to 0.001 and the standard deviation σ to 1.8 for the implementation.

We propose to use the position and the displacement of an object to model the probability density $p_{\mathbf{S}}(\varphi|\mathbf{X}_{t-1})$. Let us denote by (x_{t-1}, y_{t-1}) and (x_t, y_t) the cartesian coordinates of an object in the plane at times $t-1$ and t , respectively. The angle θ and the distance d of the displacement between the two locations can be trivially derived from the coordinates of the object at times $t-1$ and t :

$$\theta = \arctan\left(\frac{y_t - y_{t-1}}{x_t - x_{t-1}}\right), \quad (22)$$

$$d = \sqrt{(y_t - y_{t-1})^2 + (x_t - x_{t-1})^2}, \quad (23)$$

where $\theta \in [0..2\pi]$ and $d \in \mathbb{R}^+$. The local and behavioral features of the feature vector $\mathbf{X}$ are thus defined as follows:

$$\mathbf{S} = \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} \quad \text{and} \quad \varphi = \begin{pmatrix} d \\ \theta \end{pmatrix}. \quad (24)$$

Note: the behavioral feature could be extended to other features such as the object size.

3.1. Abnormal Behavior Detection on Synthetic Data

In this section, the system was trained and tested on different scenarios with over 5000 trajectories, each of them composed of an average of 70 elementary displacements. These scenarios include roads, intersections, roundabouts, junctions, etc. In the training phase, the pdf $p_{\mathbf{S}}(\varphi|X_{t-1})$ is estimated, generating a different mapping for each scenario. For instance, Fig. 1 shows the local estimate of the pdf $p_{\mathbf{S}}(\varphi|X_{t-1})$ for different locations on the map after learning of the scenario. The probability distribution was

Fig. 2. Some examples of abnormal behavior detection. The map is first trained with samples representing the trajectory of cars on the road: white dots indicate normal behavior (i.e., a car driving on the right side of the road) and black dots indicate abnormal behavior (i.e., a car driving on the wrong side of the road).

modeled with five Gaussians and the threshold τ was set to 0.015. It is also important to note that the distribution is scaled by the length of the image diagonal for d and by 2π for θ so that the distribution spans $[0..1] \times [0..1]$.

The GMM in Fig. 1(d) has 5 modes corresponding to the preferred directions at the location shown in Fig. 1(a). The GMM in Fig. 1(e) shows a bi-modal distribution for the forked road in Fig. 1(b). Finally, the distribution in Fig. 1(f) is quasi uni-modal with a main mode and a residual mode due to the integration of the neighborhood (from opposite lane) in the distribution.

We tested the performances of the algorithm on normal and abnormal trajectories. Some results are presented in Fig. 2. The scenario models a flow of cars on the horizontal road (orange). The cars drive on the left side of the road. The scenario is particularly challenging because the flows on each side of the road are adjacent. A global estimate of the pdf is not suitable to detect abnormal behavior in this case. Normal elementary behavior is labeled with a white dot whereas abnormal behavior is labeled with a black dot. It can be inferred from Fig. 2 that the proposed algorithm accurately detects when a car drifts on the opposite lane. For instance, Figs. 2(a) and 2(b) display normal trajectories. Fig. 2(c) and 2(d) show the selectivity of the algorithm with respect to the position of the vehicle in the scene.

3.2. Abnormal Behavior Detection from Video Sequences

In this section, we present an application of the proposed system to abnormal behavior detection on highways. The system is trained with real data from the *HighwayII* sequence.¹ The trajectories of the cars are extracted by background subtraction [11] and blob labeling. The entire map is trained with 49 of the extracted trajectories, and it is tested on two remaining trajectories. Fig. 3 shows the elementary displacements for the two trajectories; the results confirm that the system correctly detects normal behavior. In

Fig. 3(a), 50 elementary displacements are detected as normal whilst only 2 as abnormal (false detection). In Fig. 3(b), 30 elementary displacements are detected as normal whilst only 1 as abnormal. This means an error rate of 3.6% (3 out of 83) on the displacement. However, both trajectories are identified as normal since their classification is based on the running average of the displacement.

Fig. 3. Examples of normal behavior on a real video sequence (*HighwayII*). White dots represent normal displacements and black dots abnormal displacements.

Fig. 4 displays some abnormal paths detected by the system. Since the original video sequences contain trajectories displaying normal behavior only, synthetic data has been generated to simulate abnormal behavior. Fig. 4(a) represents a pedestrian walking on the highway. The system detects the abnormal event because of the low speed of the pedestrian. Indeed, the displacement fits the local distribution in terms of angle θ but not in terms of distance d . The pedestrian is detected as an abnormal event with 954 abnormal elementary displacements and 46 normal ones. The system thus provides a detection rate of 95.4%. Figure 4(b) represents an animal crossing the highway. In this case, the angle θ does not fit its marginal distribution. The system detects 22 normal elementary displacements for 289 abnormal

¹ Available at: <http://www.uow.edu.au/~philippe/research/videos/>

Fig. 4. Examples of abnormal behavior on a real video sequence (*HighwayII*): (a) is an abnormal behavior from a pedestrian. (b) is the trajectory of an animal crossing the highway.

ones, which corresponds to a detection rate of 92.9%; as a consequence, the trajectory is considered abnormal.

4. CONCLUSION

This paper presented a new technique for abnormal behavior detection based on local information. In contrast with existing techniques, the proposed algorithm processes separately local and behavioral features. As a consequence, the proposed approach estimates the local probability distribution of behavioral features by integration of neighborhood information. The spatio-temporal Gaussian mixture model used in the proposed algorithm is updated temporally as well as spatially, hence allowing a gradual transition in the probability distribution. Tested on synthetic and real data, the proposed algorithm gives excellent results for abnormal behavior detection.

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