ON BEHAVIOR ANALYSIS IN VIDEO SURVEILLANCE

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Abstract

With the large number of surveillance cameras now in operation, both in public placesand in commercial centers, significant research efforts have been invested in attempts to automate surveillance video analysis. The goal of visual surveillance is not only to put cameras in the place of human eyes, but also to accomplish the entire surveillance task as automatically as possible. Recently, the problem of analyzing behavior in videos has been the focus of several researchers' efforts. They concentrate on developing intelligent visual surveillance systems to replace traditional passive video surveillance systems which can only store surveillance videos but are not able to identify or describe interesting activities. In this paper, we give a survey of behavior analysis work in video surveillance and compare the performance of the state-of-the-art algorithms on different datasets.Furthermore, useful datasets are analyzed in order to provide help for initiating research projects.

Keywords - Behavior Analysis, Video Surveillance, Action Recognition, Event Detection

1 INTRODUCTION

Video surveillance is the process of monitoring the behavior of people and objects within public places, such as airports, shopping centers and crowded sports events, by cameras usually for safety and security purposes. As the amount of video data collected daily by surveillance cameras increases, the need for automatic systems to detect and recognize suspicious activities performed by people and objects is also increasing.

The back-bone of a general video surveillance system consists of sixconsecutive steps [1]: backgroundmodel, foreground pixel extraction, object segmentation, object classification, object tracking, and action recognition. The first step is to build the background model. The purpose of the background model is to represent what the environment looks like without any foreground objects. In the literature, there are many methods that are proposed for constructing the background model [2-6]. The numerous approaches to this problem differ in the type of background model and the procedure used to update the background model. The methods generally fall into two main categories according to its capability to adapt with the environment variations: adaptive and non-adaptive [1]. That is, the ability of the background model to be updated to reflect the environment changes.

The second step in image understanding process is the foreground pixel extraction. It involves the extraction of pixels that are not part of the background model from an image that is being processed. These pixels serve as a basis for further analysis in the following steps. There are several approaches to foreground pixel extraction that researchers use(such as: temporal differencing, background subtraction, Gaussian BM subtraction, optical flow) [4, 7, 8].

The third step is object segmentation. It is the process of grouping similar foreground pixels into homogenous regions, better known as foreground objects or blobs. The similarity of the foreground pixels is determined by using a similarity metric. Similarity metrics are used to determine whether the pixels being compared belong to the same blob and to group the pixels into homogenous regions where all pixels have similar characteristics. Several similarity metrics, found in literature, are used for object segmentation, some of which are color based, proximity or location based, or mixture of characteristics [1, 9].

The fourth step is object classification. It is the process of identifying what kind of object is present in the environment. This is particularly useful when distinctly different types of objects exist in the environment and when a different tracking method is used for each type of objects. Therefore, it can be considered an optional step that is performed according to the application nature. There are two main categories of approaches for classifying moving objects: shape-based classification and motion-based classification [9, 25]. In addition, many metrics are found in literature for object classification: size metric [25], speed metric [11], and dispersedness [10].

The fifth step is object tracking. It is the process of locating a moving object (or multiple objects) over time. The objective of video tracking is to associate target objects in consecutive video frames. The association can be especially difficult when the video frame rate is slow relative to objects motion. Another situation that increases the complexity of the problem is when the tracked object changes orientation over time. The most critical issue in object tracking is to make sure that the same blob is being tracked in each subsequent frame by using object matching techniques (proximity-based techniques, prediction-based techniques, blob's characteristics based techniques, or blob model based techniques) [11, 12].

The sixth step of a general video surveillance system is the action recognition. It involves the analysis and the recognition of motion patterns to produce a high-level description of actions and interactions among objects. It is the process of recognizing the actions to understand what is happening in an environment [9]. In some circumstances, it is necessary to analyze the behaviors of people and determine whether their behaviors are normal or abnormal.

Behavior analysis using visual surveillance involves the most advanced and complex researches in image processing, computer vision, and artificial intelligence. The research in this area focuses mainly on the development of methods for analysis of visual data in order to extract and process information about the behavior of physical objects (e.g., humans & vehicles) in a scene. Behavior analysis is not restricted to only video surveillance systems but it can be extended to include interactive video games and many other applications. The behavior analysis in uncontrolled environments is critical to video-based surveillance systems, which is one of the extreme goals of vision technologies. The challenges can be summarized in two points:

a) The vast diversity of one event viewed from different view angles, at different scales, and with different degrees of partial occlusions.
b) The demand for efficient processing of huge amount of video data [1].

Extensive research has been reported on behavior analysis. This paper provides a survey of the various studies in this promising area. It presents an overview of current advances in the field.

The rest of the paper is organized as follows: in Section 2, different action representation methods arediscussed showing the strengths and weaknesses of each method. Section 3 reviews the state-of-the-art methods for action recognition. Section 4 presents the datasets that are currently used by many of the action recognition approaches as a benchmark. Finally, we conclude the paper in Section 5.

2 BEHAVIOR REPRESENTATION

This section presents a review of representation methods used to discriminate actions from visual data. A first step in action recognition is the extraction of image features that are discriminative with respect to posture and motion of the objects.

Before recognizing any activity, the activity representation method must be determined. Activity representation concerns the extraction, selection, and transformation of low-level visual properties in video to construct intermediate input to an activity recognition model [9]. Activity representation should be expressive enough to describe a variety of activities yet sufficiently discriminative in distinguishing different individual activities. Various representations have been suggested. Some representations focus on maximizing the amount of high level information they could represent while others focus on maximizing the extraction efficiency.[13].

Different activity representations can be grouped into three categories as shown in Fig. 1: object based representations [9, 14], pixel based representations [15-17, 20, 21], and other feature representations [22, 24]. In the following subsections, we review the work presented in each category.

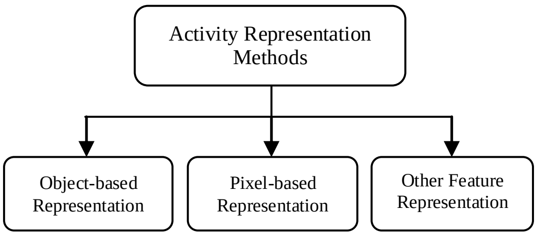


Fig. 1. Activity representation methods

2.1 Object Based Representation

This type of representation depends on extracting a set of features for each object in the video. These features include trajectory or blob-level descriptors such as bounding box and shape. A trajectory-based feature is prevalently utilized to represent the motion history of an object in a scene [14]. Usually, a trajectory is formed by associating a set of attributes of detected object, such as appearance features and velocity over successive frames using motion tracking algorithms (Fig. 2). However, these attributes are highly dynamic and vary over time. So probabilistic frameworks such as Kalman Filter and Particle Filter are commonly adopted [9]. In addition, processing steps such as moving average smoothing, or trajectory merging are commonly employed to overcome noise problem or trajectory discontinuity problem to a certain degree.

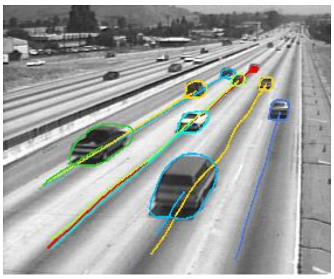


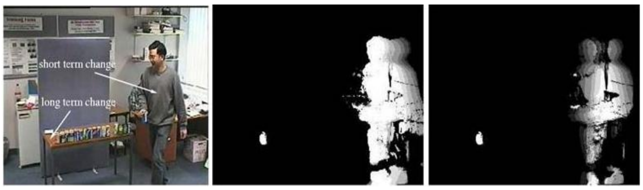
Fig. 2. Different trajectories for the movements of vehicles on the road

Object trajectories provide rich spatiotemporal information about an object's activity. Therefore, trajectory information is typically employed to understand object's behavior in the scene over time. However, using object-based representation in real-world surveillance can be challenging. Generally, object tracking depends on two important assumptions: the first one is that the object location can be determined reliably, and the second is that the spatial displacement of the same object between successive frames is small [11]. However, these assumptions are often invalid due to severe occlusions and low-frame rate surveillance videos. Specifically, the large number of objects with complex activities causes difficult and continuous inter-object occlusions (sometimes known as dynamic occlusions). Tracking of multiple objects in this environment is challenging since dynamic occlusions can cause ambiguities on the number and identities of targets, leading to temporal discontinuity in trajectories [12]. Also, given low-frame rate video, large spatial displacements of the object are detected between consecutive frames, causing severe fragmentation of object trajectories.

2.2 Pixel Based Representation

Pixel-based representation involves extracting pixel-level features such as color, texture, and gradient [9]. It does not gather features into blobs or objects like object-based representation. In the literature, the pixel-based representation methods can be categorized into three classes: foreground estimation, optical flow, and image appearance-based features.

The most common pixel-based representation is foreground pixels estimation through background subtraction. Despite its simplicity, it shows encouraging results in detecting unusual event by representing activity using both spatial and temporal distribution of foreground pixels. Many studies have shown the feasibility of this simple representation in human motion recognition [15] using Motion History Image (MHI) and in unusual event detection using Pixel Change History (PCH) or average behavior image (Fig.3) [16]. In an MHI, pixel intensity is a function of the motion history at that location, where brighter values correspond to more recent motion. However, the MHI is a special case of the PCH. A PCH image is equivalent to an MHI image when the accumulation factor is set to 1. Foreground pixel-based representation is attracting lot of attention because it avoids explicit object segmentation and tracking and it is computationally feasible. Hence, It can be efficiently employed in representing activity in crowded scenes where tracking is a complicated problem.



(a) (b) (c)

Fig. 3. (a) A keyframe of a person shopping a can (b) MHI (c) PCH

Another common pixel-based method for activity representation is optical flow. It extracts the motion information (direction and speed) of individual pixels between successive frames (Fig. 4). An image space is usually divided into cells of a specific size (e.g., 10 × 10). For each cell, the average or median flow field is computed. Then, flow vectors are normally filtered based on a predefined threshold to reduce potential observation noise. Moreover, the extracted optical flow information is usually combined with a foreground mask so that only the vectors caused by foreground objects are considered, while all the flow vectors outside the foreground mask are set to zero [17]. Like foreground pixel-based representation, optical flow based representation avoids explicit tracking of individual objects. Hence, it is also used in highly crowded scenes with broad clutter and dynamic occlusions. However, optical flow has an additional advantage over foreground pixel-based representation. It already provides information about motion direction and speed, which are essential for understanding certain types of activity. In the other hand, most optical flow methods face problems in dealing with videos with very low frame rate and poor image quality. This is because they assume small object displacement and constant brightness for the computation of velocity field, which is invalid for these videos.

Fig. 4. Optical flow representation

A more recent direction in pixel-based representation method is utilizing image appearance-based features. In [18], Histogram of oriented gradient (HOG) features are utilized to detect unusual events in web-camera videos. Space time intensity gradients are applied as salient features to a nonparametric distance measure for learning the disparity between activities [19]. Also, spatiotemporal gradients of pixel intensities are extracted from video to characterize activities in extremely crowded scene [20]. Mixture of dynamic texture is utilized to represent activity patterns [21]. In general, studies in this direction show promising results. However, calculating such mixtures of texture or space-time gradients may be computationally expensive. Furthermore, the extraction of spatiotemporal gradient would definitely fail as a result of motion discontinuities given a low frame rate video.

2.3 Other Feature Representation

Some studies replace the low-level features representations (such as location, shape, and motion) with more complex ones for efficient modeling of complex behaviors. Kim et al. [22]apply a mixture of probabilistic principal component analyzers (MPPCA) algorithm to learn a generative model for local optical flow patterns, which offers a compact representation by encoding the optical flow patterns as probabilistic words. Another relatively close work is presented in [23], the authors introduce an event-based abstraction that represents a behavior pattern using the probabilities of different classes of event occurring in each video. Different types of behavior patterns are either composed by different classes of events, or having different order of event occurrence. Also, Park et al. [24]presents a framework that switches between trajectory-based features (e.g. velocity and position) and blob-based features (e.g. aspect ratio of bounding box and height) based on the visual quality of detected objects.

3 ACTION RECOGNITION

The problem of analyzing behaviors in video has been the focus of several researchers' efforts and several systems have been described in the literature. The existing methods for action recognition in realistic, uncontrolled video data can be categorized into three categories: human model based methods, holistic methods, and local feature methods (Fig. 5) [25]. Human model based methods employ a full 3D or 2D model of human body parts, then action recognition is carried out using information of body part positioning as well as movements. Holistic methods use knowledge about the localization of humans in video and consequently learn an action model that captures characteristic, global body movements without any information of body parts. Local feature methods are entirely based on descriptors of local regions in a video, no prior knowledge about human positioning nor of any of its limbs is given. In the following subsections, these categories are discussed in more detail.

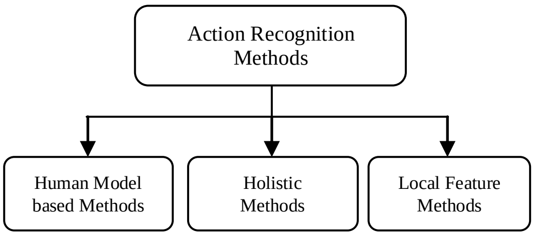


Fig. 5. Action recognition methods

3.1 Human Model Based Methods

Human model based methods recognize actions by employing information such as body part positions and movements. A significant amount of research is dedicated to action recognition using trajectories of joint positions, body parts, or landmark points on the human body with or without a prior model of human kinematics [26, 37]. Approaches in this field depend on a previous psychophysical work on visual interpretation of biological motion. This work shows that humans are able to recognize actions from the motion of a few moving light displays attached to the human body.

The localization of body parts in movies has been investigated in the past and some works have shown impressive results [27]. However in general, the detection of body parts is a difficult problem in itself, and results are still limited especially for the case of realistic and less constrained video. Some recent approaches try to improve their results by assuming particular motion patterns, hence improving body parts tracking. However, this also limits their application to action recognition [25].

3.2 Holistic Methods

Holistic methods do not require the localization of body parts. Instead, global body structure and dynamics are used to represent human actions [25]. The main idea is that, global dynamics are discriminative enough to characterize human actions, given a region of interest centered on the human body. Moreover, holistic representations are much simpler than other approaches that explicitly use a kinematic model or information about body parts, since they only model global motion and appearance information. Therefore their computation is in general more efficient and robust. This characteristic is especially important for realistic videos in which background clutter, camera ego-motion, and occlusion make the localization of body parts difficult.

In general, holistic approaches can be roughly divided into two categories. The first category employs shape masks or silhouette information, stemming from background subtraction or difference images, to represent actions [2, 28]. The second category is mainly based on shape and optical flow information [29, 36].

3.3 Local Feature Methods

Local space-time features keep characteristic shape and motion information for a local region in video. They provide a relatively independent representation of events with respect to their spatio-temporal shifts and scales as well as background clutter and multiple motions in the scene. These features are usually extracted directly from video and hence avoid possible failures of other pre-processing methods such as motion segmentation or human detection [30]. In the literature, various approaches are proposed under this category [33, 35, 38].

4 ACTION DATASETS

The methods of evaluating the performance of object detection, object tracking, object classification, and behavior and intent detection and identification in a visual surveillance system are more complex than some of the well-established biometrics identification applications, such as fingerprint or face, due to uncontrolled environments and the complexity of variations found in the same scene [13]. Due to the increasing research in video surveillance systems over the last years, there are several public datasets that try to evaluate the performance of such systems. These datasets are necessary to fairly evaluate algorithms under different conditions and to compare new algorithms with existing ones.

The datasets used to evaluate the behavior analysis work can be classified as being either surveillance datasets (such as PETS, TRECVid) or action recognition datasets (such as Weizmann, KTH, UCF, YouTube, Hollywood) [1, 9, 25]. In addition, some of the datasets are designed only for specific surveillance applications: driver assistance systems, people detection walking through a busy pedestrian zone, very specific scenarios or even very general video security systems.

PETS dataset (Performance Evaluation for Tracking and Surveillance) (http://www.cvg.rdg.ac.uk/slides/pets.html) isa good starting place when looking into performance evaluation. PETS has several good datasets for both indoor and outdoor tracking evaluation and event/behavior detection. PETS datasets include outdoor people and vehicle tracking using single or multiple cameras, indoor people tracking (and counting) and hand posture classification, annotation of a smart meeting, including facial expression, gaze and gesture/action, multiple sensor (camera) sequences for unattended luggage, multiple sensor (camera) sequences for attended luggage removal (theft), and multiple sensor (camera) sequences for loitering. In addition to PETS datasets, there are efforts, like TRECVid evaluation datasets (http://trecvid.nist.gov/), with the goal to support the development of technologies to detect visual events through standard test datasets and evaluation protocols.

The Weizmann actions dataset (http://www.wisdom.weizmann.ac.il/~vision/SpaceTimeActions.html) includes ten different types of action classes: bending downwards, running, walking, skipping, jumping-jack, jumping forward, jumping in place, galloping sideways, waving with two hands, and waving with one hand (Fig.6). Each action class is performed once (sometimes twice) by 9 subjects. In total, the dataset consists of 93 video sequences. The background in the videos is homogeneous and static. In the original experimental setup by the authors, testing is carried out using leave-one-out cross-fold validation approach, i.e., testing is performed for one sequence at a time while training is executed on all remaining sequences. Performance is given in terms of average accuracy (error rate).

Fig. 6. Example images from the Weizmann dataset

The KTH actions dataset (http://www.nada.kth.se/cvap/actions/) consists of six different human action classes: walking, jogging, running, boxing, waving, and clapping (Fig. 7). Each action class is performed several times by 25 subjects resulting in 2391 video samples in total. The sequences were recorded in four different scenarios: outdoors, outdoors with scale variation, outdoors with different clothes, and indoors. The background is homogeneous and static in most sequences. In the original experimental setup by the authors, samples are divided into a test set (9 subjects: 2, 3, 5, 6, 7, 8, 9, 10, and 22) and training set (the remaining 16 subjects). Evaluation on this dataset is done via multi-class classification. Classification performance is evaluated as average accuracy over all classes.

Fig. 7. Example images from the KTH dataset

The UCF sport actions dataset (http://crcv.ucf.edu/data/UCF_Sports_Action.php) contains ten different types of human actions: swinging (on the pommel horse and on the floor), diving, kicking (a ball), weight-lifting, horse-riding, running, skateboarding, swinging (at the high bar), golf swinging and walking. The dataset consists of 150 video samples that show a large intra-class variability. The performance criterion for the multi-class task is the average accuracy over all classes. The original setup employs leave-one-out approach for testing.

The YouTube dataset (http://crcv.ucf.edu/data/UCF_YouTube_Action.php) contains 11 action categories: basketball shooting, biking/cycling, diving, golf swinging, horseback riding, soccer juggling, swinging, tennis swinging, trampoline jumping, volleyball spiking, and walking with a dog. This dataset is challenging due to large variations in camera motion, object appearance and pose, object scale, viewpoint, cluttered background, illumination conditions etc. It contains a total of 1600 video sequences. In the original setup, the evaluation is performed using cross validation for a set of 25 folds that is defined by the authors. Average accuracy over all classes is used as performance measure.

The Hollywood1 dataset (http://www.di.ens.fr/~laptev/actions/) contains eight different action classes: answering the phone, getting out of the car, hand shaking, hugging, kissing, sitting down, sitting up, and standing up. Action samples have been collected from about 32 different Hollywood movies. In total, the full dataset contains 663 video samples, divided into a clean training set (219 sequences) and a clean test set (211 sequences), where training and test sequences were obtained from different movies. The additional noisy training set consists of 233 sequences.

Hollywood2 (http://www.di.ens.fr/~laptev/actions/hollywood2/) is the extended version of Hollywood1 dataset. It consists of video samples collected from 69 different Hollywood movies. The initial eight action classes were extended by adding four additional ones: driving car, eating, fighting, and running. In total, there are 2517 action samples split into a manually cleaned training set (823 sequences) and a test set (884 sequences). The noisy training set contains 810 sequences. Train and test sequences are obtained from different movies. The performance for both, Hollywood1 and Hollywood2, is evaluated by computing the average precision for each of the action classes and reporting the mean AP over all classes.

Table 1 shows comparative results of different methods on different datasets. The two popular datasets, which are currently used by most of the approaches are: Weizmann and KTH datasets, however both are all not very realistic and share strong simplifying assumptions, such as static background, no occlusions, given temporal segmentation, and only a single actor [13]. Note that several authors report high performance exceeding 90% for both Weizmann and KTH datasets while the performance is degrading for UCF, YouTube, and Hollywood datasets (Fig.8). That is, the UCF sports dataset is a collection of TV sport events. It offers a large variety of action classes while being limited in its size. Also, the YouTube and Hollywood datasets are considered the most challenging and extensive datasets published in the literature.

Table 1. State-of-the-art results on different datasets reported as average accuracy achieved

Year	Reference	Dataset used	Accuracy achieved
2008	[31]	UCF	71%
2009	[32]	UCF	66%
2009	[33]	Hollywood1	53.5%
		KTH	94.5%
2009	[34]	Hollywood1	47.5%
		KTH	94.1%
2009	[35]	Youtube	86.6%

2010	[36]	Weizmann	97.4%
2010	[37]	Weizmann	87.7%
2010	[38]	Weizmann	94.5%
		Youtube	87.27%
2010	[39]	Weizmann	97%
2010	[40]	Youtube	86.9%
2011	[41]	Weizmann	95.1%
2011	[42]	Weizmann	89.3%
2011	[43]	Weizmann	97%
		Youtube	88%

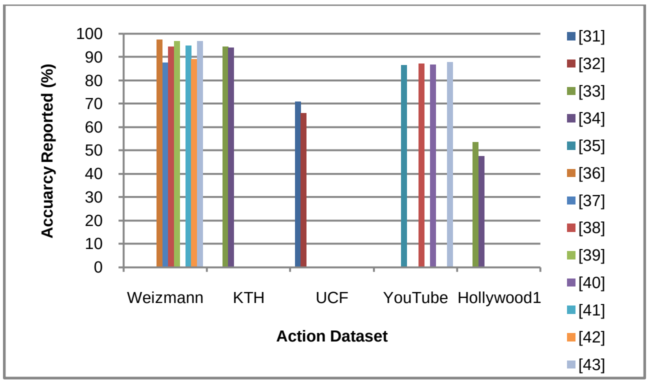


Fig. 8. Accuracy reported for each action dataset

Although behavior analysis techniques perform rather strongly in selected datasets, a real-world behavior analysis is still extremely challenging, due to complicated environments, cluttered backgrounds, occlusions, illumination changes, multiple activities, and numerous deformations of an activity.Simplifying the problem by adding more assumptions may significantly improve the results but it will limit its applicability in real world. The algorithms developed thereforeoften have specific strengths and limitations, and are designed for particular domain. A particular algorithm maybe optimal for a specific application and may perform effectivelywithout modification. However, due to the complex nature of manyenvironments, adaptive and/or hybrid forms of existing behavior representation and action recognitionapproachesmay best be able to meet the needs of dynamically changing conditions.This survey has identified the need for further research in thisdirection, which will require a comprehensive analysis of the specificenvironment, and its dynamic nature, prior to the determinationof optimal combinations taking into account the real-time challenge.

5 CONCLUSION

The area of behavior analysis in video surveillance is a fast growing research area.In this paper, we present a survey of some of the important studies in the area by grouping them in consistent contexts.We have classified approaches with respect to how they representthe actions, and how theyrecognize actions from a video stream,Although many proposed behavior analysis techniques perform strongly in selected datasets, a real-world surveillance video archive is still extremely challenging, due to complicated environments, cluttered backgrounds, occlusions, illumination changes, multiple activities, and numerous deformations of an activity.

Despite clear advances in the field of action recognition, evaluation of these methods remains mostly heuristic and qualitative. Most of the datasets do not include ground-truth and detailed pose information for the researchers. There is a need to find some meaningful datasets and areas to work, rather than keeping efforts in trivial action recognition datasets.

To sum up, with investigating all of dominant algorithms which are widely used in behavior analysis, the survey reveals important progress made in the last five years. However, many issues are still open and deserve further research. future work needs to come up with moreefficient ways to detect complex actions where there issome interaction between different blobs in an environment.Also, more research should be directed tosolve difficulties in behavior detectionsuch as the strong appearance variation in semantically similar events (e.g., people performing actions with different clothing), the viewpoint variation, and the duration of the action. Finally, robust and realistic surveillance datasets are needed to effectively evaluate different proposed methods.

This survey can be considered as a starting point for those interested in pursuing further work in this area and it suggests that further exploration is still required. Behavior analysis will continue to remain an active research area since the computer understanding of behavior is exceedingly important for many military and civil applications.

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