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A Perlustration of Ingenious Video Surveillance

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ABSTRACT

Video surveillance has long been in use to oversee security sensitive areas such as banking, departmental stores, highway patrol's, public places and borders. Video surveillance system is the most substantial issue in native security field. The improvements in computing power, availability of large-capacity repository devices and high speed network communications tiled the way for low-cost, multi sensor video surveillance systems. Conventionally, the video outputs are processed online by human operators and are usually saved to tapes for later use only after a judicial event. The accretion in the number of cameras in ordinary surveillance systems overloaded both the human operators and the storage devices with high volumes of data and made it absurd to ensure proper overseeing of sensitive areas for long times. For filtering out useless information generated by an array of cameras, and increase the response time to judicial events, assisting the human operators with identification of important events in video by the use of "ingenious" video surveillance systems has become a critical requirement. In this paper, an ingenious visual surveillance system with real-time moving object apprehension, categorization and tracking capabilities is presented. In addition to these, some important needs of a booming ingenious video surveillance system are met.

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INTRODUCTION

Video surveillance systems have long been in use to oversee security sensitive areas. The antiquity of video surveillance consists of three geneses of systems which are called 1GSS, 2GSS and 3GSS.The first genesis surveillance systems (1GSS, 1960-1980) were based on analog sub systems for image acquisition, transmission and processing. They protracted human eye in dimensional sense by broadcasting the outputs of several cameras overseeing a set of sites to the displays in a central control room. The next genesis surveillance systems (2GSS, 1980-2000) were hybrids in the sense that they used both analog and digital sub systems to resolve some drawbacks of its predecessors. Third genesis surveillance systems (3GSS, 2000-) provide end-to-end digital systems. Image procurement and processing at the sensor level, communication through mobile and fixed amalgamate broadband networks and image cache at the central servers benefit from low cost digital framework. The eventual aim of 3GSS is to allow video data to be used for online alarm generation to assist human operators and for offline analysis effectively. In order to achieve this goal, 3GSS will provide ingenious systems that are able to generate real-time alarms defined on convoluted events and handle appropriated storage and content-based retrieval of video data.

The making of video surveillance systems "ingenious" involves quick, dependable and vigorous algorithms for moving object apprehension, categorization, tracking and activity analysis. Moving object apprehension is the basic step for further analysis of video. This creates a target of attention for higher level processing but also decreases computation time considerably. Commonly used techniques for object apprehension are background deduction, analytical models, momentary differencing and ocular flow. Due to vital environmental conditions such as change in illumination, shade and wave tree branches in the wind object segmentation is a difficult and significant problem that needs to be handled well for a booming visual surveillance system. Object categorization categorizes detected objects into predefined classes such as human, vehicle, animal, clutter, etc. Currently, there are two major methods towards moving object categorization, which are outline-based and mobility-based methods. Outline-based methods make use of the objects' 2D spatial information whereas mobility-based methods use momentary tracked features of objects for the categorization solution. The advances

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in the development of these algorithms would lead to breakthroughs in applications that use visual surveillance. Detecting the natural phenomenon flame besides normal object mobility would be an advantage for a visual surveillance system the presented system is capable of perceiving flame in indoor and outdoor environments. Present flame detection algorithms are based on the use of color and simple mobility information in video. In addition to perceiving flame colored moving regions, the method presented in this paper analyzes the mobility patterns, the momentary periodicity and spatial variance of high-frequency behavior extensively.

Moving Object Apprehension:

Each application that benefit from ingenious video processing has different needs, thus requires different treatment. Thus, identifying regions that correspond to motion objects such as people and vehicles in video is the foremost step of almost every ocular system since it provides a target of attention and simplifies the processing on consecutive analysis steps. Due to charismatic changes in habitual scenes such as sudden illumination and weather changes, repetitive motilities that cause clutter, mobility detection is a difficult problem to process reliably. Frequently used methods for moving object detection are background deduction, analytical methods, momentary differencing and ocular flow whose descriptions are given below.

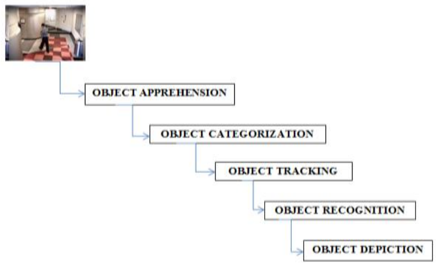

Fig: 1. A generic architecture for ingenious video processing.

A. Background Detection:

Background deduction is particularly a commonly used technique for mobility segmentation in static scenes. It attempts to detect moving regions by deducing the current image pixel-by-pixel from a reference background image that is created by averaging images over time in an initialization period. The pixels where the dissimilarity is above a threshold are classified as foreground followed by generating a foreground pixel map, some semantic post processing operations such as deterioration, distension and closing are performed to reduce the effects of noise and enhance the detected regions. The allusion background is updated with new images over time to adapt to charismatic scene changes. There are different approaches to this basic scheme of background deduction in terms of foreground region discovery, preserving the backgrounds and post processing. Here we use the simple version of this scheme where a pixel at location (a, b) in the current image It is marked as foreground if,

$$|It(a, b) - Bt(a, b)| > \breve{\imath}$$

Is satisfied where ĭ is a predefined threshold. The background image BT is updated by the use of an Unlimited Impulse Response (UIR) filter as follows:

$$Bt+1 = \alpha It + (1 - \alpha)Bt$$

The foreground pixel outline creation is followed by semantic closing and the expulsion of small-sized regions. Although background deduction techniques perform well at extracting most of the relevant pixels of moving regions even they stop, they are usually sensitive to vital changes when, for instance, inactive objects uncover the backgrounder sudden illumination changes occur.

B. Analytical Methods:

More advanced methods that make use of the analytical characteristics of individual pixels have been developed to overcome the shortcomings of basic background deduction methods. These analytical methods are mainly inspired by the background deduction methods in terms of keeping and dynamically updating statistics of the pixels that belong to the background image methods. Foreground pixels are known by contrasting each pixel's statistics with that of the background model. This method is popular due to its trustworthiness in scenes that contain noise, illumination changes and shadow.The system uses an analytical background model where each pixel is represented with its minimum (Mi) and maximum (Ma) intensity values and maximum intensity difference (Md) between any consecutive frames observed during initial training period where the scene contains no autonomous objects. A pixel in the current image It is classified as foreground if it satisfies:

$$|Mi(a, b) - It(a, b)| > Md(a, b)$$
$$|Ma(a, b) - It(a, b)| > Md(a, b)$$

After thresholding, a single iteration of semantic erosion is applied to the inspected foreground pixels to remove pixel noise. In order to grow the deteriorated regions to their prime sizes, a sequence of deterioration and distention is performed on the foreground pixel outline. Also, small-sized regions are eliminated after applying connected component labeling to locate the regions. The statistics of the background pixels that belong to the non-moving regions of current image are updated with new image data. As another example of analytical methods, an adaptive background mixture model for real-time tracking. Every pixel is separately modeled by a mixture of Gaussians which are refurbished online by received image information. In order to detect whether a pixel belongs to a foreground or background methods, the Gaussian distributions of the mixture model for that pixel are assessed.

C. Momentary Differencing:

Momentary differencing attempts to detect motion regions by making use of the pixel-by-pixel difference of subsequent frames in a video series. This method is highly flexible to vital scene changes; however, it generally fails in detecting whole compatible pixels of some types of motion objects. A sample object for inaccurate mobility disclosing is shown in Figure 2. The mono colored region of the human on the left hand side makes the momentary differencing algorithm to fail in excerpting all pixels of the dynamics of the human. Also, this method is unsuccessful in detecting stopped objects in the scene. Supplementary methods need to be endorsed in order to detect stopped objects for the progress of higher level on the left hand side since it is uniform colored. The detected motion objects are marked with white pixels.

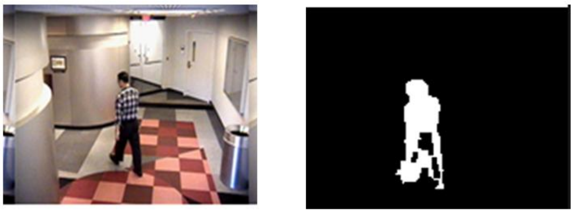

Fig. 2: Moving object detection in the outdoor environment with fake motion: (a) the original image of three consecutive frames, (b) the temporal differencing results of the original image.

Lipton *et al*. presented a two-frame differencing scheme where the pixels that satisfy the following equation are marked as foreground.

$|I_t(a, b) - I_t{-}1(a, b)| > \breve{\imath}$

In order to overcome shortcomings of two frame differencing in some cases, three frame differencing can be used [3]. For instance, Collins *et al*. developed a hybrid method that combines three-frame differencing with an adaptive background deduction model for their VSAM project. The hybrid algorithm successfully segments moving regions in video without the defects of momentary differencing and background deduction.

D. Ocular Flow:

Ocular flow methods make use of the flow vectors of moving objects over time to detect moving regions in an image. They can detect mobility in video sequence seven from a moving camera, however, most of the ocular flow methods are computationally complex and cannot be used real-time without specialized hardware (Rama, K.G.S., 2006).

E. Obscurity and Light Change Detection:

The algorithms described above for mobility detection perform well on indoor and outdoor environments and have been used for real-time surveillance for years. However, without special care, most of these algorithms are susceptible to both provincial and universal illumination changes. Shadows cause the mobility detection methods fail in segmenting only the moving objects and make the upper levels such as object categorization to perform inaccurate. The prospective methods in the literature mostly use either intensity[6] or stereo information to cope with obscurity and sudden light changes. Horprasert *et al*. present a novel background deduction and obscurity detection method. In their method, each pixel is represented by a color model that separates brightness from the intensity component. A given pixel is classified into four different categories by calculating the distortion of brightness and intensity between the background and the current image pixels. They make use of the observation that an area cast into shadow results in significant change in intensity. They also use the gradient information in moving regions to ensure trustworthiness of their method in cryptic cases. The method presented in [6] adopts a obscurity detection scheme which depends on two heuristics: a) pixel intensity values within obscurity regions tend to decrease in most cases when compared to the background image, b) the intensity reduction rate changes smoothly between neighbouring pixels and most shadow edges do not have strong edges.

An efficient method to deal with obscurities is using stereo as presented inW4S (Ramoser, H., 2003) system. In some systems, a universal light change is inspected by counting the number of foreground pixels and if the total number exceeds some threshold, the system is reset to adapt to the sudden illumination change.

Object Categorization:

Moving regions detected in video may correspond to variant objects in real-world such as strollers, vehicles, clutter, etc. It is very important to recognize the type of a detected object in order to track it trustworthily and analyze its activities correctly. Currently, there are two major approaches towards moving object categorization which are outline-based and mobility-based methods. Outline-based methods make use of the objects' 2D spatial information whereas mobility-based methods use momentarily tracked features of objects for the categorization solution.

A. Outline Based Categorization:

Common features used in outline-based categorization schemes are the bounding rectangle, area, silhouette and gradient of detected object regions. The approach presented in makes use of the objects' silhouette contour length and area information to classify detected objects into three groups: human, vehicle and other. The method depends on the assumption that humans are, in general, smaller than vehicles and have complex outlines. Dispersedness is used as the categorization cadent and it is defined in terms of object's area and contour length (perimeter) as follows:

Dispersedness =Perimeter2/Area:

Categorization is performed at each frame and tracking results are used to improve momentary categorization consistency. The categorization method uses view dependent visual features of detected objects to train a sensory network classifier to recognize four classes: human, human group, vehicle and clutter. The inputs to the neural network are the dispersedness, area and aspect ratio of the object region and the camera zoom magnification. Like the previous method, categorization is performed at each frame and results are kept in a histogram to improve momentary regularity of categorization. Saptharishi *et al*. propose a categorization scheme which uses a logistic linear sensory structure trained with Differential Learning to recognize two classes: vehicle and people. Another categorization method proposed by Brodsky *et al*. uses a Radial Basis Function (RBF) classifier which has a similar framework like a three-layer back-propagation structure. The input to the classifier is the normalized gradient image of the detected object regions.

B. Mobility Based Categorization:

Some of the methods in the literature use only momentary mobility features of objects in order to recognize their classes. In general, they are used to distinguish non-stiff objects from stiff objects. The method proposed in is based on the momentary self-similarity of a moving object. As an object that exhibits periodic mobility evolves, its self-similarity measure also shows a periodic mobility. The method exploits this clue to categorize moving objects using frequency. Ocular flow analysis is also useful to distinguish stiff and non-stiff objects. A. J. Lipton proposed a method that makes use of the local ocular flow analysis of the detected object regions. It is expected that non-stiff objects such as humans will present high average residual flow whereas stiff objects such as vehicles will present little residual flow. Also, the residual flow generated by human mobility will have a periodicity. By using this cue, human mobility, thus humans, can be distinguished from other objects such as vehicles.

Flame Detection:

The number of papers that discuss flame detection using video is very few in computer vision literature. Most of the prospective methods exploit the color and mobility features of flame. Healey *et al*. use a model which is based only on color characteristics of flame. Obviously this method generates false alarms due to flame colored regions. Unimproved approach which makes use of mobility information as well as the color property is presented by Philips *et al*. Recently, Liu and Ahuja presented a method that defines spectral, spatial and momentary models of flame to detect its presence in video. The spectral model is represented in terms of flame pixel color probability density. The spatial model describes the spatial structure of a flame region and the momentary model captures the changes in the spatial structure over time.

Object Tracking:

Tracking is an important and arduous problem that arouses interest among computer vision researchers. The objective of tracking is to establish accord of objects and object parts between consecutive frames of video. It is a significant task in most of the surveillance applications since it provides cohesive momentary data about moving objects which are used both to enhance lower level processing such as mobility segmentation and to enable higher level data extraction such as activity analysis and behavior recognition. Tracking has been an arduous task to apply in clogged situations due to inaccurate apportionment of objects. Common problems of erroneous apportionment are long obscurities, partial and full occlusion of objects with each other and with stationary items in the scene. Thus, dealing with shadows at mobility detection level and coping with occlusions both at apportionment level and at tracking level is important for booming tracking. Tracking in video can be categorized according to the needs of the applications it is used in or according to the methods used for its solution. Complete body tracking is generally adequate for rustic video surveillance whereas objects' chunk tracking is necessary for some domestic surveillance and higher level behavior understanding applications. There are two common methods in tracking objects as complete (Bodor, R., 2003): ones based on correspondence pairing and other one carries out unambiguous tracking by making use of position prediction or mobility calculation. On the other hand, the methods that track chunks of objects employ model-based schemes to locate and track body chunks. Some example models are stick figure, Cardboard Model and volumetric models.W4 combines mobility estimation methods with correspondence pairing to track objects. It can track chunks of people such as heads, hands, torso and feet by using the Cardboard Model which represents relative positions and sizes of body chunks. It keeps appearance templates of individual objects to handle pairing even in merge and split cases. Stauffer *et al*. employs a linearly anticipative multiple interpretation tracking algorithm. The algorithm assimilates size and positions of objects for seeding and maintaining a set of Kalman filters for mobility calculation. Also, Extended Kalman filters are used for trajectory prediction and occlusion handling in the work of Rosales and Sclaroff .

Conclusion And Future Work:

In this work, we presented a set of methods and tools for an "ingenious" visual surveillance system. Our tests in sample applications show that using nearest neighbor matching scheme gives assuring results and no complicated methods are necessary for complete-body tracking of objects. Also, in handling simple object occlusions, our chart-based correspondence matching approach recognizes the distinctiveness of objects entered into an occlusion successfully after a split. However, due to the nature of the heuristic we use, our occlusion manipulating algorithm would fail in differentiating occluding objects if they are of the same size and color. Also, in cramped scenes handling occlusions becomes infeasible with such an approach, thus a pixel-based method, like ocular flow is required to identify object segments accurately. We proposed a novel object categorization algorithm based on the object outline similarity. The method is generic and can be applied to different categorization problems as well. Although this contrivance gives assuring results in categorizing object types, it has two hindrances: (a) the method requires effort to create a labeled template object database (b) the method is view reliant. If we could have eliminated (b), the first problem would automatically vanish since one universal template database would suffice to classify objects. One way to achieve this may be generating a template database for all possible silhouettes of different classes. This would increase the computational time, but may help to overcome the need for creating a template database for each camera position separately. The flame detection algorithm we presented is based on an existing method but contains a novel extension which reduces the false alarm rates considerably compared to the method discussed in. Especially, checking the flame colored regions for momentary periodicity and spatial variance and using persistency of flame regions to raise alarms are the novel parts of our method which increases the overall reliability of the fire detection system. The system can be made more booming by incorporating different flame color spectrums and fusion of thermal images. In short, the methods we presented for "ingenious" visual surveillance show assuring results and can be both used as part of a real-time surveillance system or utilized as a base for more advanced research such as activity analysis in video.

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