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Video Surveillance System Using Motion Detection –A Survey

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Abstract- **Now a days, much of the video surveillance systems require to manually setting a motion detection sensitivity level to generate motion alarms. The performance of motion detection algorithms, embedded in CCTV camera and digital video recorder usually depends upon the preselected motion sensitivity level, which works in all environmental conditions. Due to the preselected sensitivity level, false alarms and detection failures usually exist in video surveillance systems. The proposed motion detection model based upon variational energy provides a robust detection method at various illumination changes and noise levels of image sequences without tuning any parameter manually.We analyze the structure mathematically and demonstrate the effectiveness of the proposed model with numerous experiments in various environmental conditions. Due to the compact structure and efficiency of the proposed model, it could be implemented in a small embedded system.**

Keywords: **Energy minimization, motion detection, segmentation, variational energy, video surveillance.**

I. INTRODUCTION

Video monitoring systems are a necessity in the modern times. Although some people object the idea of 'being watched', surveillance systems actually improve the level of public security, allowing the system operators to detect threats and the security forces to react in time. Surveillance systems evolved in the recent years from simple CCTV systems into complex structures, containing numerous cameras and advanced monitoring centers, equipped with sophisticated hardware and software. However, the future of surveillance systems belongs to automatic tools that assist the system operator and notice him on the detected security threats. This is important, because in complex systems consisting of tens or hundreds of cameras, the operator is not able to notice all the events. [1]

Surveillance systems are widely used to monitor threats by using CCTV cameras to prevent criminal activity in airports, subway stations, large complex malls, for examples. Surveillance systems are continually being developed with such security issues, but we need a more accurate automated system. In a typical video surveillance system, image sequences are transmitted to a surveillance center and displayed on several video monitor screens. Hundreds of video channels displayed on several monitor screens are continuously observed by Security guards.

In commercial, law enforcement, and military applications there are immediate needs for automated surveillance systems .Mounting video cameras is cheap, but finding available human resources to observe the output is expensive. Although surveillance cameras are already prevalent in banks, stores, and parking lots, video data currently is used only "after the fact" as a forensic tool, thus losing its primary benefit as an active, real-time medium. What is needed is continuous 24-hour monitoring of surveillance video to alert security officers to a burglary in progress or to a suspicious individual loitering in the parking lot, while there is still time to prevent the crime. In addition to the obvious security applications, video surveillance technology has been proposed to measure traffic flow, detect accidents on highways, monitor pedestrian congestion in public spaces, compile consumer demographics in shopping malls and amusement parks, log routine maintenance tasks at nuclear facilities, and count endangered species.

We need to achieve high detection rates and simultaneously low false alarm rates while developing the model of motion detection, both of these conventional methods often fail to satisfy in noisy environment. To overcome such difficulties, we introduce a variational energy model with robust environmental changes and low dependency on parameters and variation in signal-to-noise ratio. One of the strong points of such modeling is that any pre- or post-process is not required because the energy itself explains a desired state and entire process, so one may point out that such a variational model has complexity and innate nonlinearity, so it is not proper to apply on real time response task. But fine segmentation is not main concern for our purpose. Our goal is to detect objects in motion reliably.

II. RELATED MODEL

In an image sequence moving objects generate image difference detecting each connected component in the difference considering regarding the intensity and size is the key issue in many motion detection algorithms. Thus, one may view the problem as segmentation or clustering problem. In this section, we discuss the related models to our new model and address challenges.

First we consider a piecewise constant image with the Gaussian white noise. In other words, there is a high intensity contrast between objects and background in the image. If we consider its intensity histogram, intensity values are clustered at the mean value of each object. If the noise is moderate enough one may partition by using the k-means clustering algorithm

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - \mu_i\|^2$$

Where xi is the intensity of each pixel in the image S = $\{S_1, S_2, \ldots \ldots \ldots S_K\}$ is a partition of the given image, and μ_i is the mean of S_i Since it watches only intensity values, it may overlook the geometry of each segment in the image so that it is hard to catch clean boundaries and remove small blobs by noise [13]. If one makes the problem harder by introducing low contrast with high noise, it is much harder to find means to set a decision boundary value. Other thresholding methods have similar problems without a proper post process or decision rule, if they watch only statistical information.

III. BUILDING A ROBUST MOTION TRACKER

` A robust video surveillance and monitoring system should not depend on careful placement of cameras. It should also be robust to whatever is in its visual field or whatever lighting effects occur. It should be capable of dealing with movement through cluttered areas, objects overlapping in the visual field, shadows, lighting changes, effects of moving elements of the scene (e.g., swaying trees), slow-moving objects, and objects being introduced or removed from the scene. Thus, to monitor activities in real outdoor settings, we need robust motion detection and tracking that can account for such a wide range of effects. Traditional approaches based on backgrounding methods typically fail in these general situations. Our goal is to create a robust, adaptive tracking system that is flexible enough to handle variations in lighting, moving scene clutter, multiple moving objects, and other arbitrary changes to the observed scene. The resulting tracker is primarily geared toward scene-level video surveillance applications. [5]

Segmentation used in this model is the art of automatically separating an image into different regions in a fashion that mimics the human visual system. It is therefore a broad term that is highly dependent on the application at hand, e.g. one might want to segment each object individually, groups of objects, parts of objects, etc.. In order to segment a particular image, one must first identify the image before a set of rules can be chosen to target this goal. The human eye uses low-level information such as the presence of boundaries, regions of different intensity or colors, brightness and texture, etc., but also mid-level and high-level cognitive information for example, to identify objects or to group individual objects together. As a direct consequence, there are a wide variety of approaches to the segmentation problem.[9]

A common element of the surveillance systems is a module that performs background subtraction for differentiating background pixels, which should be ignored, from foreground pixels, which should be processed for identification or tracking. The difficult part of background subtraction is not the differencing itself, but the maintenance of a background model – some representation of the background and its associated statistics. We call this modeling process background maintenance.

IV. PROPOSED MODEL

Here we propose a new model for reliable, robust and fast segmentation, which is irrespective of the noise and contrast variations of an image and detects a rough shape feature of a moving object. Let μ be the absolute difference between current image and background image. We assume that μ is a real-valued function defined on a rectangular domain Ω= (0, N)*(0, M),, where N and M are the numbers of pixels along a horizontal and vertical direction, respectively. We will represent a segmented region as the positive set {ø >0} of the function which is achieved by minimizing the following energy functional:

$$E(\phi) = \gamma \, Reg(\phi) + Eth(\phi)$$

$$= \gamma \int |\nabla \phi|^2 dx$$

$$+ \int B[\mu, \phi](x)\, \phi(x)\, H(\alpha + \phi(x))\, dx$$

$$- \int T[\mu, \phi](x)\, \phi(x)\, H(\alpha - \phi(x))\, dx \qquad (3)$$

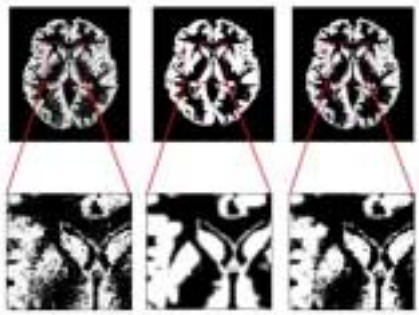

Fig. 1: noisy image and the segmentation results by E(ø).

Where

B [μ ,ø](x) = $(|\mu(x) - c^{+}(ø)|^{2}$ + C/2)/ ($|\mu(x) - c^{+}(ø)|^{2}$+$|\mu(x) - c^{-}(ø)|^{2}$+C) (4)

T [μ ,ø](x) = $(|\mu(x) - c^{-}(ø)|^{2}$ + C/2)/ ($|\mu(x) - c^{+}(ø)|^{2}$+$|\mu(x) - c^{-}(ø)|^{2}$+C) (5)

And

$$c^{+}(ø) = \frac{1}{|\Omega^{+}_{ø}|}\int \mu(x)dx$$

$$c^{-}(ø) = \frac{1}{|\Omega^{-}_{ø}|}\int \mu(x)dx$$

Here $\Omega^{-}_{ø}$:={ø ≤ 0} , $\Omega^{+}_{ø}$:={ø > 0} and α is a constant to represent an indicator value for segmentation, ø = -α to the background and ø = α to the targets. Is C a small positive constant to guarantee positiveness of B[μ,ø] and T[μ,ø] . We fix α=1 and C=10^{-6} in all computational examples. . Γ is the only tuning parameter but we choose γ= 0.7 in all computational examples. That is what we mean by low dependency upon parameters and robustness to environmental change.

Variational methods have been extensively used and studied in image processing in the past decade because of their flexibility in modeling and various advantages in the numerical implementation. Examples of this include image segmentation, object tracking texture synthesis and vector field visualization. The basic idea of variational methods is to minimize a cost or energy functional. This functional generally will depend on the features of the image. The classical way to solve the minimization problem is to solve the corresponding Euler-Lagrange equation. This PDE based method sometimes is not very efficient because of numerical stability constraints.

Roughly speaking, the first term of (3) handles irregularity and spurious small blobs and the role of the last two terms is to find a thresholding value and separates the domain into two pieces. If γ is small enough, the model may discern details but not single out noise, close to thresholding methods. If relatively large, the model may lose details but suppress noise [2]. In other words, γ is inversely proportional to the size of noisy blobs to remove. The value γ= 0.7 is a moderate value between them found by statistical tests in Chapter 4.1. One may see the role of each part in Fig. 1.

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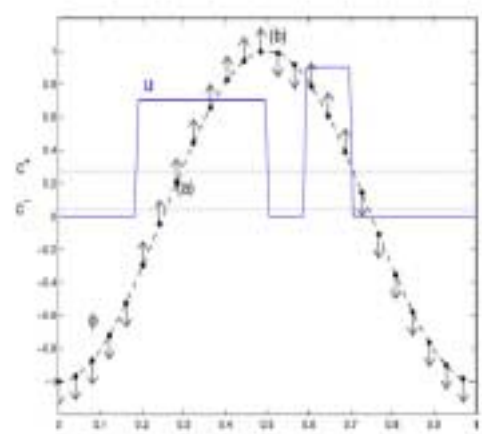

Fig. 2. Solid line: μ,

V. Algorithm and Various Parameters

In this model, the entire region evolves. The role of the shifted Heaviside functions H[α+ø] and H [α+ø] is to bound the range of the function in [-α,α] for numerical and analytical stability. In other words, it is a barrier. For a fast numerical computation, drop those two functions and enforce ø=α if ø(x)>α and ø(x)=-α the simplified energy functional is

E (ø) = γ $\int |\nabla ø|^{2}$dx

$$+\int\left(\frac{|\mu(x)-c^{+}|^{2}+\frac{C}{2}}{(|\mu(x)-c^{+}|^{2}+|\mu(x)-c^{-}|^{2}+C)}-\frac{|\mu(x)-c^{-}|^{2}+\frac{C}{2}}{(|\mu(x)-c^{+}|^{2}+|\mu(x)-c^{-}|^{2}+C)}\right)\phi(x)dx$$

(6)

Algorithm: Motion detection algorithm

Generate a difference image μ

Initialize ϕ^{0}: $\phi^{0}(x)$ =α if μ(x) ≥ θ and $\phi^{0}(x)$ =-α if μ(x) < θ

While ϕ^{n} is not stationary do

Compute $c^{+}{}_{n}$:= $c^{+}(\phi^{n})$ and $c^{-}{}_{n}$:= $c^{-}(\phi^{n})$

Compute ϕ^{n+1}

$$\phi^{n+1}= \phi^{n} + \Delta t *(\gamma \Delta \phi^{n}-\left(\frac{|\mu-c_{n}{}^{+}|^{2}+\frac{C}{2}}{(|\mu-c_{n}{}^{+}|^{2}+|\mu-c_{n}{}^{-}|^{2}+C)}-\frac{|\mu-c_{n}{}^{-}|^{2}+\frac{C}{2}}{(|\mu-c_{n}{}^{+}|^{2}+|\mu-c_{n}{}^{-}|^{2}+C)}\right))$$

Bound ϕ^{n+1}: ϕ^{n+1}(x) =α if ϕ^{n+1}(x)> α and ϕ^{n+1}(x) =-α if ϕ^{n+1}(x) <-α

End while.

LIMITATIONS

The given model fails when the background consists of swaying trees and fountains. Since the certain backgrounds as mentioned above are continuously in motion with undeterminable background, model may not give the result as its full efficiency. Here the problems are directly related to background modeling.

CONCLUSION

As per the limitation is that it does not detect continuous motion, so this can be overcome in the future work. Due to the compact structure and the efficiency of the proposed model, it could be implemented in a small embedded system and it provides real time motion segmentation. For more reliable motion detection algorithm, it is needed to adjust the background estimation following statistical changes in image sequences.

To reduce false alarms and detection failure in various environmental conditions, motion detection method based upon variational energy is developed. The energy functional of the proposed model is designed to provide motion detection without tuning parameters so as to have environmental robustness. Future work includes the characterization of the statistics in background modeling and incorporating such statistical information in a new model. In this way the survey has been taken of this video surveillance system.

REFERENCES

[1] Multi-Stage Video Analysis Framework Andrzej Czyzewski, Grzegorz Szwoch, Piotr Dalka, Piotr Szczuko,Andrzej Ciarkowski, Damian Ellwart, Tomasz Merta, Kuba £opatka, £ukasz Kulasek and Jêdrzej Wolski Gdansk University of Technology, Multimedia Systems Department, Poland

[2] Environmentally Robust Motion Detection for Video Surveillance Hyenkyun Woo, Yoon Mo Jung, Jeong-Gyoo Kim, and Jin Keun Seo

[3] A. Tse, "The real world of critical infrastructure," Security Products (May 2006) [Online]. Available: http://www.secprodonline.com/articles/41517/

[4] B. Song and T. F. Chan, "A fast algorithm for level set based optimization," CAM Rep. 02-68.

[5] C. Stauffer and W. E. L. Grimson, "Learning patterns of activity using real-time tracking," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 8, pp. 747–757, Aug. 2000.

[6] C. Wren, A. Azarbayejani, T. Darrell, and A. Pentland, "Pfinder: Realtime tracking of the human body," IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 780–785, Jul. 1997.

[7] D. Wang, T. Feng, H. Shum, and S. Ma, "A novel probability model for background maintenance and subtraction," in Proc. 15th Int. Conf. Vis. Interface, 2002, pp. 109–117.

[8] E. Stringa, "Morphological change detection algorithms for surveillance applications," in Proc. Brit. Mach. Vis. Conf., 2000, pp. 402–410.

[9] F. Gibou and R. Fedkiw, "A fast hybrid k-means level set algorithm for segmentation," in Proc. 4th Ann. Hawaii Int. Conf. Stat. Math., 2005,pp. 281–291.

[10] G. Halevy and D. Weinshall, "Motion of disturbances: Detection and tracking of multibody non-rigid motion," Mach. Vis. Appl., vol. 11, pp. 122–137, 1999.

[11] G. L. Foresti, "Object detection and tracking in time-varying and badly illuminated outdoot environments," Opt. Eng., vol. 37, pp. 2550–2564, 1998.

[12] H. Woo, J. K. Seo, and M. O. Lee, "Method and apparatus of real-time segmentation for motion detection in surveillance camera system," Patent Pending May 2007.

[13] T. F. Chan and L. A.Vese, "Active contour without edges," IEEE Trans. Image Process., vol. 10, no. 2, pp. 266–277, Feb. 2001.

[14] J. Heikkila and O. Silven, "A real-time system for monitoring of cyclists and pedestrians," in Proc. 2nd IEEE Workshop Vis. Surveill., Jul.1999, pp. 74–81.